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VOLUMETRIC RISK AND WEATHER DEPENDENCY ON RETAIL ELECTRICITY MARKETS

Kansantaloustieteen
Pro Gradu –tutkielma
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Syksy 2004

Hyväksytty Kansantaloustieteen laitoksen johtajan päätöksellä 26/10 2004

arvosanalla erinomainen (90 p.)

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TIIVISTELMÄ

17.10.2004

VOLYYMIRISKI JA SÄÄRIIPPUVUUS SÄHKÖMARKKINOILLA

Tutkimuksen tavoitteet

Tutkimuksen tavoitteena on käsitteellisesti määritellä ja kvantitatiivisesti analysoida volyymiriski sekä löytää käytännöllinen tapa sen taloudellisten vaikutusten minimoimiseksi sähkön vähittäismyyjälle. Vaikka monet tekijät vaikuttavat toimitettavan volyymin vaihteluista aiheutuvien tappioiden suuruuteen, tämä tutkimus rajoittuu tarkastelemaan yksinomaan ulkolämpötilan vaihteluiden vaikutuksia. Tutkielmassa mallinnetaan Vattenfall Sähkönmyynti Oy:n tuloksen lämpötilariippuvuutta. Yrityksen kokemat mittavat tappiot talvella 2002-2003 ovat motivoineet tätä tutkimusta.

Lähdeaineisto ja menetelmät

Tutkimuksen teoria pohjautuu akateemiseen kirjallisuuteen, asiantuntijoiden artikkeleihin, alan julkaisuihin ja kokemukseen. Lämpötiladata perustuu Tampereen Härmälän sääaseman havaintoihin ajalta 1979-2004. Hintatiedot ja muu data on saatu Vattenfall-konsernin tietokannoista.

Lämpötilariskiä analysoidaan regressiomallilla ja samanaikaisella kuorman sekä hintojen simuloinnilla. Lämpötila toimii kuorman pääasiallisena selittäjänä ja ns. välimuuttujana hintamallissa. Lisäksi hintayhtälöön on sisällytetty hydrologista tilannetta kuvaava luku, mikä edesauttaa lämpötilan vaikutuksen eristämistä. Kuorman ja hintojen yhteisjakauman simuloinnilla saadaan esiin tappioiden jakauma eri olosuhteissa, ja lämpötilojen simuloinnilla saadaan todennäköisyys olosuhteille.

Tulokset

Sähkömarkkinoiden vapautuminen on voimistanut volyymiriskiä, kun volyymivaihteluita täydentää hintojen kasvanut volatiliteetti. Volyymiriski määritellään tulona volyymin ja hinnan poikkeamista odotusarvoistaan. Toisaalta vähittäismyyjä häviää joutuessaan täydentämään ennalta suojattua hankintaansa kalliilla spot-sähköllä, kun kiinteillä hinnoilla myytävän sähkön kulutus kasvaa. Toisaalta ylijäänyttä energiaa joudutaan aika ajoin myymään takaisin tappiolla. Volyymiriski liittyy siis läheisesti myyjän kykyyn ennustaa asiakkaidensa kulutusta. Riskiä pahentaa kuorman ja hintojen epälineaarinen suhde.

Tulokset paljastavat, että lämpötilariski on epälineaarinen, ja että tappioiden jakauma on huomattavan vino. Erityisesti kylmyyteen liittyvä riski on suuri, kun taas poikkeamat lämpimämpään eivät ole niin vakavia. Perinteiset vakuutukset ja sähköjohdannaiset eivät ole suositeltavia volyymiriskin hallintavälineiksi. Sen sijaan standardoidut lämpötilajohdannaiset toimivat hyvin simulointien valossa, ja niillä on myös oletettavasti jonkinasteista likviditeettiä kansainvälisillä markkinoilla.

Avainsanat

Volyymiriski, Sääjohdannainen, Sähkömarkkinat

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ABSTRACT

17.10.2004

VOLYMETRIC RISK AND WEATHER DEPENDENCY ON RETAIL ELECTRICITY MARKETS

Objectives

The aim of this thesis is to conceptually define volumetric risk, quantitatively analyse it and to identify a way to mitigate its influence on electricity retailers' profits. While the magnitude of losses attributable to volumetric fluctuations is determined by several factors, this thesis concentrates on temperature-induced volumetric risk alone. Vattenfall Sales is used as a case company throughout the text and the study is motivated by the great losses the winter 2002/2003 brought about for the company.

Data and Methodology

The theoretic framework of the study is based on academic literature, articles from practitioners, industry publications, as well as experience. The temperature data is obtained from one of the official weathers station in Tampere, Finland, and covers the period 1979-2004. Other data is drawn from the databases of the Vattenfall group.

The analysis of exposure to temperature is performed by employing a regression model and joint simulation of load and prices. Temperature is used as the primary explanatory variable in the load equation and as a proxy for system load in the price equation. In addition, hydrological conditions are included in the price equation, which makes it possible to better separate the influence of temperature. A joint simulation of prices and load is carried out to reveal the distribution of losses under different circumstances and the probabilities of each condition are obtained by simulating temperature.

Results

Volumetric risk is defined as the product of volume and price deviations from their expected values. On one hand, a retailer loses money when it needs to complement hedged procurement with expensive spot electricity to fulfil its delivery obligations. On the other hand, sometimes surplus energy must be resold to the market at a loss. Therefore, volumetric risk is related to the retailer's ability to forecast demand, which in turn is highly correlated with temperature. The exposure is made worse by the non-linear relationship between prices and load.

The results reveal the highly non-linear nature of the exposure and the significant skew of the loss distribution. Particularly, the risk related to cold temperatures is found to be significant, while the opposite is true for warmer conditions. Traditional insurances and electricity derivatives are deemed inappropriate tools for managing temperature exposure. In contrast, standard heating degree day swaps and options are recommended, as they do well in simulations and they are also more likely to have some liquidity than more structured products.

Key Words

Volumetric Risk, Weather Derivatives, Electricity Markets

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Tables and Figures

1 INTRODUCTION

1.1 Background

The deregulation of electricity markets that began in the beginning of 1990's, following the initial steps taken by the U.K., has exposed the industry to a whole lot of new risks that used be latent in the past. While the financial results of electric utilities have always been susceptible to weather conditions, Rookley (2000) maintains that the impact of weather is now even more pronounced as volumetric variations are coupled with higher price volatilities. Prices, which are at present purely a function of supply and demand, can become extremely volatile since electricity cannot be directly stored for later use.

Volumetric risk derives from the inability to reliably forecast future demand (e.g. De Martini 2002). Explicitly, electricity to retail consumers is sold as open delivery and prices are often fixed at the moment of writing contract. Hence, if wholesale prices end up being higher than retail prices and at the same time realised volumes are higher than hedged volumes, the retailer loses money on every extra kilowatt-hour consumed. Even if the retailer had own generation capacity, it would forego the opportunity of selling to the wholesale market instead.

The link to weather is provided by temperature, which is the main determinant behind customer load (Dischel 1999a). Moreover, the non-storability of electricity causes the prices to be highly dependent on system load[1]. In consequence, peaks in demand tend to coincide with high prices, which further aggravates volumetric risk. On the other hand, at times of lower-than-expected consumption the surplus energy must be resold at a loss.

Despite the energy business being so gravely affected by weather, current research has given sparse attention to analysing specific shapes of weather exposure. Rather, the focus has been on generic weather derivative products that can be used as building blocks for hedging strategies in a variety of business areas. On one hand, this thesis aims at partly filling the gap in conducted research. On the other hand, weather risk is highly company-

[1] System load denotes the instantaneous effect in the whole power system within a certain region. Customer load refers to the load of a particular supplier. The sum of all customer loads equals system load.

specific, implying that no general result is directly applicable to the entity underlying this thesis and so a specific study is needed.

1.2 Motivation and Objectives

Vattenfall Sales will be used as a case company throughout the text. It lost a significant amount of money in the course of winter 2002/2003, as volumetric risk materialised thanks to extremely cold weather. Moreover, Vattenfall was not the only energy retailer to suffer from the coldness. Reportedly, also the sales unit of Fortum Oyj had to enter millions in losses into its books because of unfavourable weather conditions (Fortum Oyj 2003).

Motivated by the significance of the issue to electricity retailers, the purpose of this thesis is to propose means to mitigate temperature-induced volumetric risk. The study is divided into two major objectives. The first objective is to thoroughly define volumetric risk both conceptually and quantitatively. The intention is to obtain a focus for the rest of the study and to find what the exposure means in economic terms to an electricity retailer. Subsequently, the second objective is to explore and perform comparisons on different approaches to managing the exposure. Ultimately, the aspiration of this study is to identify a feasible solution to levelling the effect of temperature on retailer profits.

Both of the named objectives will deserve an equal emphasis. One should not dismiss the importance of thoroughly defining and quantifying the exposure. The completion of this work reveals the graveness of the exposure and forms the basis of the second part of the research. The second part, in turn, will take the results of the first part a step further. Both market-based and other solutions to the management of the exposure to temperature will be considered.

1.3 Structure

This thesis is divided into six chapters. The current chapter provides the background of the study, as well as its objectives, employed methods and limitations. The second chapter gives a thorough overview of the Nordic electricity market. It first describes the development of the legal framework and then offers a detailed account of the functioning principles. Chapter three presents the current state of the weather market. Besides conveying general information on the market, some of the commonest weather contract types are introduced.

Chapter four drills down to the essence of the thesis. First, a thorough definition of volumetric risk is given. Next, the model that lies in the centre of the study is described and the analysis of temperature exposure is performed. The shape of the exposure and the distribution of losses related to temperature deviations are shown. Chapter five, in turn, forms the second part of the study. A few alternative solutions are suggested and those that seem realistic are tested. Chapter five ends with recommendations. Finally, chapter six concludes.

1.4 Research Methods

As mentioned before, no like research has been published to date. This means that fresh ideas and the proper application of available methods are required. Rookley (2000) discusses similar exposure and develops a model for its assessment. However, Rookley does not try to separate the different sources of the risk, such as temperature. In addition, Rookley leaves the modelling of the expected spot price rather ambiguous.

Several econometric and mathematical methods are employed in this study and it is presumed that the reader is comfortable with those methods. The theory of the thesis mainly draws on academic literature and articles from practitioners, as well as on research already accomplished within Vattenfall. The data is obtained from the Nordic electricity market, an official Finnish weather station and internal databases of Vattenfall.

1.5 Limitations

The results presented in this thesis are not directly applicable to other purposes, but must be reproduced with appropriate data. Moreover, volumetric risk is quite many-faceted and this study is restricted to an investigation of the exposure to temperature alone. Therefore, some parts of the model, such as spot price simulation, are not universally valid, but only capture the properties essential to temperature exposure.

Also, this is by no means exclusively an econometric study. Rather, statistical tools will be employed only to the extent practically justifiable, as the intention is to build an approximating model that can be used for practical purposes. The scope of the study does not allow for the pursuit of statistical perfection.

2 THE NORDIC ELECTRICITY MARKET

2.1 Market Profile

In terms of population the Nordic countries are relatively small, but the level of electricity consumption is quite high. More precisely, the annual consumption in the integrated Nordic power market amounts to 380 TWh, which corresponds to the size of the power market in the U.K. Factors contributing to the high per capita consumption include an energy intensive industry structure, a cold climate with long and dark winters, as well as a high share of electricity in total energy consumption. The latter is largely attributable to the vast hydropower resources primarily in Sweden and Norway. Also, electrical heating accounts for a significant share of the residential electricity consumption. (Bergman 2001, 1)

The total generation capacity in the Nordic area is around 410 TWh. In addition, links with neighbouring countries offer import facilities up to 4000 MW. However, the hydropower generation capacity may experience year-to-year variations equivalent of around +/- 20 TWh. Moreover, should two successive dry years occur, the hydropower generation can be 40 TWh lower than during a normal year. Energy supply will be secured even under extreme conditions, though, thanks to long term energy reserves and import facilities. Yet, recent years have shown that system bottlenecks could present a problem to meeting the demand for peak load capacity in some areas. Vattenfall estimates the total annual consumption to increase to around 403,5 TWh during the next 10 years. The estimate is based on the annual compilation EURPROG by EURELECTRIC. On the other hand, generation capacity is expected to grow by roughly 26 TWh. (Vattenfall AB 2003a-b)

2.2 Legislative Reform

Electricity markets in Europe have undergone some major changes during the past good ten years. According to Bergman (2001, 1), until the beginning of 1990's national electricity business was coordinated by the government and operated by closely regulated and vertically integrated generation and transmission companies. Thus, market power was a prominent feature of the Nordic market. In addition, all costs could be passed through to the customer, as pricing was based on cost and profit mark-up (Vattenfall AB 2003b, 4). These facts effectively hindered any serious development in the quality of service or efficiency.

Market liberalisation began with the Norwegian Energy Act in 1991, which opened a part of the industry to competition. Finland was next to deregulate in 1995, soon followed by Sweden and Denmark in 1996 and 1999, respectively. Although deregulation initially involved only a limited part of the market, all of the Nordic market is nowadays completely liberalised. (Vattenfall AB 2003b, 3)

In the Nordic region, the main objectives of the power market reform have been the attainment of a better balance between generation capacity and demand; increased efficiency within the power industry; and the reduction of regional differences in prices to end-users (Nord Pool 2003a, 7). Key elements of the reform have been unconditional access to the transmission grid and separation of the competitive parts, such as supply, and transmission, which is a natural monopoly (Bergman 2001, 4). Effectively, although parts of the industry were opened to competition, system control remains at national hands.

Paying heed to the experiences in the pioneering countries of the Nordic region, as well as the U.K. and the U.S., the European commission passed the Electricity Directive 96/92/EC, which aims at extending the principles of the Single Market to the energy industry (EURELECTRIC 2001). The Electricity Market Report 2003 compiled by Vattenfall AB (2003a, 9) summarises the steps to be taken across Europe, as regards deregulation of the electricity market. All customers should have right to choose their supplier, non-household customers by 1st July 2004 and households by 1st July 2007. Also, by 2007 transmission and distribution must be unbundled from competitive activities, at least in terms of legal form, organisation and decision making in all member countries.

The Nordic power co-operation began already in 1962 with the establishment of Nordel[2]. The Nordic electricity generation has traditionally been concentrated, that is, a handful of large companies have dominated the markets. It was considered that these large companies should not be split into smaller ones in order to maintain competitiveness in

[2] See www.nordel.org for more information.

the future restructured European market. A common Nordic market was seen as a solution to reduce the dominance of these large companies. (Nord Pool 2003a, 7)

In 1993, then, Statnett merged with Samkjøringen, the previous Norwegian market for electricity, to create a new company for organising the market place for electricity. The company subsequently changed its name to *Nord Pool ASA*, which Sweden joined in 1996. Sweden was followed by Finland in 1998 and Denmark in 2000. Also the U.K. participates once in a while in this Nordic market place. Nord Pool is effectively a non-mandatory power exchange and by no means a monopoly enterprise. (http://www.nordpool.com)

2.3 Functioning of the Nordic Electricity Market

In this section the relevant elements of the Nordic power market will be described. A crude division can be made into the wholesale market, which consists of a non-mandatory exchange and OTC-markets, and the retail market where suppliers and end-users usually meet.

2.3.1 Market Participants

In principle, there are eight type of participants in the wholesale market. The role of each of them will be briefly discussed below.

Regulator

The importance of a just and effective regulator must not be underplayed in the energy sector. As the transmission and distribution businesses are natural monopolies, electricity consumers have no real choice but to use the services of the local network owner. Therefore, it is imperative that the providers of these services are subject to close regulation in order to prevent them from abusing monopoly power. This abuse of power would otherwise show as discrimination or excessive prices and could severely distort competition. (European Commission 2001, 14)

Another justification for a regulating authority relates to the concept of universal services. Within the EU, special rules have been laid down to ensure that so-called public service obligations are respected. These obligations should guarantee electricity at affordable prices, security of supply, high quality of service, environmental protection and special care for the elderly and disabled, among other things. However, liberalisation and public policies are not seen as contradictory. On the contrary, it is believed that competitive forces will drive power companies to improve their quality of service rather than to ignore it. (European Commission 2001, 11-12)

Moreover, concludes a report by EURELECTRIC (2003), good regulation can help to support trading and its reputation. Regulation encourages information transparency and thus provides confidence in markets. It is carried out in partnership between national authorities and the European Commission. According to the report, it is widely acknowledged that the regulator has to be an independent body.

TSO and grid owners

In a deregulated environment, it is essential that everyone be guaranteed an equal access to the transmission grid. There are practically two alternative methods of providing access to the grid: regulated third party access (rTPA) or negotiated third party access (nTPA), the difference being the way of setting the tariffs and terms of access. The high-voltage (110 kV or 400 kV) grid, also called the *transmission grid*, is operated by the *transmission system operator* (TSO), which must be unbundled from competitive activities. Distribution system operators run the medium and low voltage wires that deliver the commodity to the final consumers. (European Commission 2001, 8)

The TSOs in Scandinavia are responsible for both the security of supply and the maintenance of the transmission grid. Hence, the TSO is also responsible for keeping the system electrically stable, i.e. ensuring that production levels correspond to those of consumption. It will be explained later under 'Regulating and Balancing Market' how this is done. TSO has to be a non-commercial organisation, neutral and independent with regard to the market participants. (Nord Pool 2003b, 2-4)

In Scandinavia, TPA is regulated and a so-called system of connection-point tariff has been introduced. The idea is that the producer pays a fee, a stamp tariff, for each kWh delivered to the grid. Respectively, the end-user pays a stamp tariff for each kWh she receives from the grid. (Nord Pool 2003b, 2)

Generators

Generators own the power plants and sell electricity to retailers, large end-users, as well as to the transmission system operator in the regulation market. They attempt to maximise their profits by trading in the spot and derivatives markets. For instance, hydro-producers usually save water when spot prices are low, so that they have more to sell when the market price is higher.

Producers are often accused of deliberately holding back generation in order to increase prices (Vattenfall 2003a, 30). Yet, as the Nord Pool is an anonymous auction, market manipulation is virtually impossible (Nord Pool 2003a, 30). Of course, generators may have an incentive to regulate production as they try to maximise their profits, but their market power is fortunately quite limited. Actually, producers serve the market by rationing scarce resources and delivering power when it is most needed. Moreover, the market mechanism ensures that plants are utilised in the order of cost. In this manner, prices rise during times of shortage and fall when there is excess capacity.

Vattenfall is the largest single electricity producer on the Nordic electricity market with a share of 20 per cent of total generation (Vattenfall 2003b, 4). The Nordic market is rather concentrated and is likely to remain so in the future, too. On the other hand, it is characteristic of the Finnish market that a large share of the production capacity is jointly owned by large industrial end-users. Hence, only a part of industrial consumption is in practice open to competition.

Retailers

Basically, retailers serve end-users based on their own generation or power purchased in wholesale markets. Larger players that have fully adopted the market-based business model have separated, at least for internal purposes, their production and retail operations. Thus, both the retailer and producer maximise their results independently. Frequently larger retailers also serve the needs of smaller ones.

It wouldn't make sense for an individual consumer to buy electricity directly from a power plant. Consequently, retailers constitute a necessary link in the value chain. However, also retailers need to make profit in order to maintain their business. In addition to direct costs and overheads, retailers require a profit margin to satisfy their investors, since the business is no longer cross-subsidised or backed by the state. In today's environment, retailers tend to make profit by adding a margin on top of their own procurement, which is most likely covered beforehand with financial contracts.

Exchange, traders and brokers

Traders and brokers are players who have emerged only after the liberalisation of the market. A trader is a participant who owns the power on the way through the trade process (Nord Pool 2003b, 1). In contrast, a broker does not own the commodity, but acts as an intermediary (Op. cit.).

The exchange provides a market where all the participants, primarily wholesale traders, can meet. Nord Pool, the common exchange in the Nordics, is the world's first integrated international power exchange. In addition to operating market places, Nord Pool provides clearing services for financial electricity contracts. Since its establishment in 1993, Nord Pool has promoted the market at least in the following ways (Nord Pool 2004a, 14):

- Provides neutral and transparent reference price
- Serves as a reliable counterparty
- Provides easy access at low transaction costs
- Serves as a grid congestion management tool
- Distributes neutral market information.

All participants fulfilling certain requirements can trade on Nord Pool's financial market. However, a physical grid connection is required from the spot market participants. In 2002, around third of the Nordic power consumption was traded via Nord Pool's spot market and roughly a similar proportion of the standardised financial contracts, i.e. forwards, futures and European options on power, were traded via its financial market (Nord Pool 2003b, 12). Nevertheless, of the estimated 3800 TWh traded in financial contracts, which corresponds to about 10 times the normal annual Nordic consumption, over 80 per cent is either traded or cleared at Nord Pool (Nord Pool 2003a, 17).

End-users

End-users comprise households, small and medium-sized enterprises, as well as large industrial users. Although a few large end-users trade via Nord Pool, as a rule they do business only with intermediaries, such as traders and retailers. The defining characteristic is that they all have a natural short position in the commodity.

2.3.2 Production Capacity

To be able to develop an understanding of the local market mechanism, it is necessary to know something about the structure of generation assets. The Nordic composition will be briefly explained here.

As was noted earlier, the generation capacity in the Nordic area amounts to around 410 TWh. In a normal year, hydropower contributes to some 50 per cent of the power required to meet the demand. However, due to variable weather conditions, the hydropower capacity swings in the range of +/- 20 TWh, as compared with a normal year. Hence, the reservoir situation has a substantial effect on seasonal spot prices.

Table 1 shows the composition of generation in 2001. Power production in Norway is almost 100 per cent hydropower. Sweden and Finland both have a mixture of hydropower, nuclear and thermal power. Denmark, in turn, although famous for renewable production, has mostly thermal plants and combined heating and power (CHP) facilities.

Country	Generation (TWh)				
	Hydro	**Thermal/ CHP**	**Nuclear**	**Renewable**	**Total**
Sweden	78,5	10	69	0,5	**158**
Norway	121	1			**122**
Finland	13	36	22		**71**
Denmark		32		4	**36**
Total	**212,5**	**79**	**91**	**4,5**	**387**
% Of Total	55 %	20 %	24 %	1 %	100 %

Table 1: Generation by means of production in 2001. Source: Nord Pool 2003a, 4.

Figure 1 illustrates the shape of the marginal cost curve based on a normal year. The order in which plants are utilised is called the *merit order*. First, the marginal cost of hydropower production is quite insignificant if not measured by opportunity loss. Also nuclear power, although requires huge initial investments, has a relatively low marginal cost. Then, the curve quickly gets steeper as production levels approach the capacity ceiling. In a normal year, supply and demand curves intersect in the band of thermal coal-fired plant. According to Vattenfall AB (2003a, 31), the marginal cost of generation in a coal-fired plant is around 20-25 €/MWh at coal prices that prevailed in the end of 2003. However, it is worth to mention that prices based on solely marginal costs will not recover long-term costs. Also, the fuel prices may swing from time to time and, consequently, the merit order may slightly change.

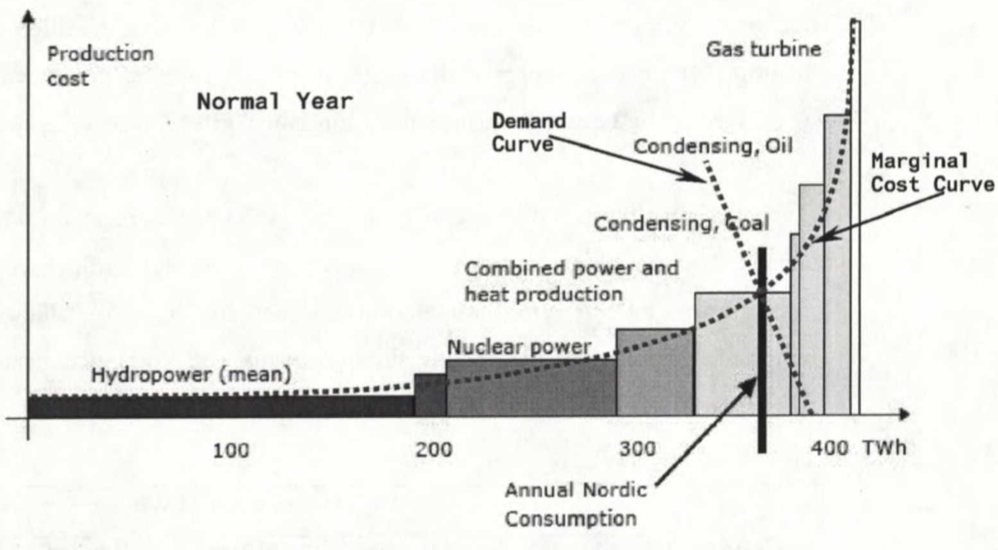


Figure 1: Marginal cost curve on the Nordic market. Source: Nord Pool 2003a, 5.

At times of weaker-than-normal hydrological balance, the share of hydropower is smaller and the supply curve becomes steeper earlier, which implies higher market price. Also, demand can experience temporary spikes, which entails the use of expensive reserve capacity and soaring prices. As is evident from basic theory of economics, the fact that the marginal cost lower down in the merit order is lower is irrelevant to the determination of the spot price. On the contrary, the market-clearing price, and the one that maximises utility to society, is found at the intersection of the supply (marginal cost) and demand curves.

One obvious problem is the relative inelasticity of demand. The possibilities of consumers to regulate their usage according to price levels are very limited. Factors that move the demand curve include cold weather and industrial activity. On the other hand, exogenous factors behind the supply curve include e.g. precipitation levels and nuclear outages.

2.3.3 Spot Market

Bidding and the system price

The spot market for power at Nord Pool is called *Elspot*. The Elspot market is a day-ahead physical-delivery power market. The primarily traded contract on Elspot is a power contract of one-hour duration, the minimum size of which is 0,1 MWh/h. Participants submit bids for the following day's individual delivery hours by 12 p.m., after which Nord Pool calculates and announces the resulting prices for each of the 24 hours in question. The procedure is more reminiscent of an auction than traditional exchange trading. (Nord Pool 2004a, 14-21)

The price determination goes as follows. Participants submit their bids for all 24 delivery hours. The bids for individual hours are usually stepwise, so that buy orders decrease at higher prices and eventually change into offers to sell (see figure 2). Alternatively, a participant can choose to make a price-independent bid for all hours. This frequently becomes relevant when the final price is already secured by an engagement in a derivatives contract. (Op. cit.)

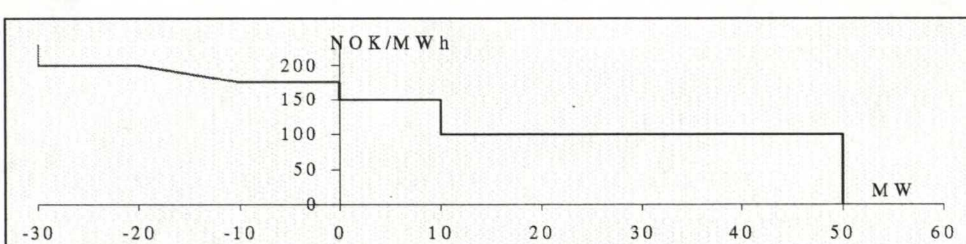


Figure 2: Bid/offer from one player for an individual hour.

The Norwegian Krone is used as the official currency on the spot market until 2006. After that, all Nord Pool contracts will be denoted in Euros.

After all bids have been submitted, Elspot establishes a bid curve for each hour using price-volume pairs from the bids. Since the bid curve of an individual participant is discrete, Elspot will use linear interpolation to calculate the prices and volumes. The so-called *system price* is determined for the entire exchange area with no regard to grid capacities. Thus, the system price is sometimes called unconstrained market price. The system price for an arbitrary hour is found at the intersection of the demand and supply bid curves (see figure 3). (Op. cit.)

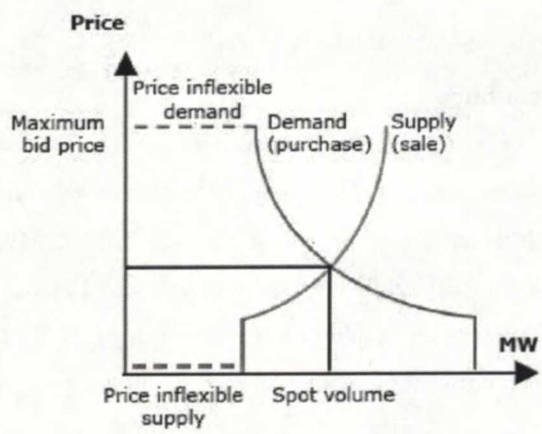


Figure 3: Calculation of the system price and volume. Source: Nord Pool 2004a, 19

Congestion management

Nonetheless, sometimes it happens that demand exceeds supply at the system price within certain areas and that grid capacity is insufficient for filling the gap. Then, to relieve *grid congestion*, a price differential is introduced to steer the power flow. There are several price areas within the Nordic area: Finland and Sweden are own areas, Denmark has two areas and Norway is split into a number of areas depending on conditions. Basically, congestion management is on the shoulders of the TSOs, but in the Nordic countries this task is assigned to the Nord Pool Power Exchange. In a liberalised environment it is essential that the capacity of a bottleneck be given to a neutral participant. This also increases the liquidity and credibility of the exchange, as it manages all the trading that goes between the areas. (Nordel 2000, 38-39)

Figure 4 below depicts the determination of *area prices* when there are bottlenecks in the interconnection capacity between price areas. Nord Pool uses an iterative method called market splitting to determine the market-clearing price for each price area. Areas are first considered separately and divided into high price areas and low price areas depending on whether there is over-demand or oversupply, respectively. Grid capacity is then used to transport maximal amount to the high price area and correspondingly export maximal amount from the low price area. The resulting prices and volumes can be read from figure 4 at points marked 'constrained equilibrium'. (Op. cit.)

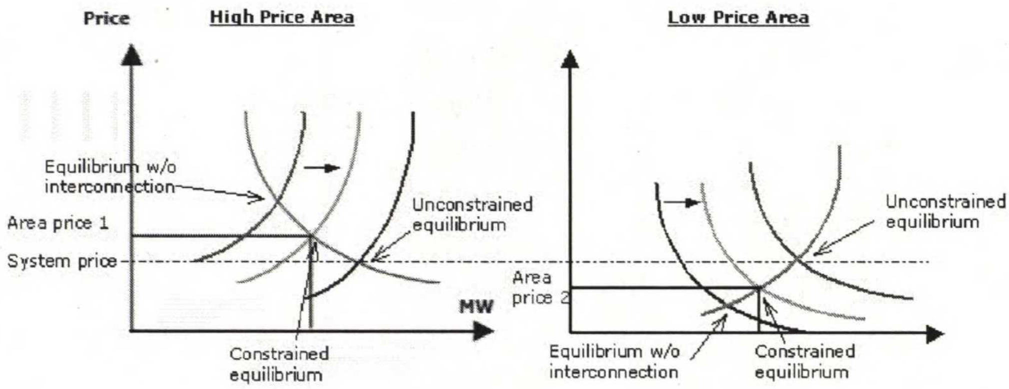


Figure 4: Congestion management at Nord Pool

Counter-trading is used to manage bottlenecks within a given price area. The TSO concerned can employ counter-trading to increase an interconnector's trading capacity, although physical power transmission over the bottleneck remains intact. In this scheme the TSO pays for down-regulation of power on the surplus side and up-regulation on the shortfall side. As a result, the whole area gets the same price. Moreover, the costs incurred by the system operator encourage further investment in interconnection capacity. (Nordel 2000, 39)

2.3.4 Regulating and Balancing Market

The fact that electricity can be bought from anywhere throughout a market area does not mean that the physical power actually flows from the seller to the buyer. Rather, what commercial partners deliver to each other and the end users are exclusively the prices (Nord Pool 2003b, 3). More specifically, owning power actually means responsibility for the power balance. In other words, the buying and selling of each participant must be equal every hour of operation.

The TSO has the liability for maintaining the power balance in the transmission network. The Finnish Electricity Market Decree (438/1998) stipulates that each open supplier must assign a balancing party who will take on the financial consequences of balance settlement. In addition, each grid area has a retailer with an obligation to deliver who will bear the financial consequences of residual balance settlement – i.e. the difference between actual power balance and allocated balance as regards the application of type-loading curves – within that grid area. Those parties who fall short in electricity are sold *balancing power* at usually higher cost compared with the prevailing market price. Respectively, those having a surplus on their balance are usually paid less than the market price for their excess power. Hence, to be competitive, it is imperative for a retailer to be able to forecast customers' consumption accurately.

The time span between Elspot trading and delivery can amount to 36 hours. However, consumption forecasts usually become more accurate as delivery draws closer and, on the other hand, balance deviations can turn out to be costly. Therefore, balancing parties might wish to trade to close the gap even after Elspot market has closed. This is exactly the idea behind the *Elbas* market for Finland and Sweden, as it enables continuous trading of physical power up to one hour before delivery (Nord Pool 2004a, 22). This balancing market is open 24 hours every day of the year (Op. cit., 23).

There is still another market, which can assist in balancing the grid. According to a Nord Pool (2004a, 30) report, the *real-time market* (a.k.a. the regulating market) has two main objectives: to serve as a tool for TSOs to maintain power balance during real-time operations and to provide a price for participants' power imbalances. National TSOs upkeep the regulating power markets and forwards the players' bids to the common Nordic real-time market (Fingrid 2004).

Participants capable of implementing a power change of 10 MW in 10 minutes can submit regulating bids no later than 30 minutes before the hour of operation. Up-regulation bids are submitted for increased production or decreased consumption and down-regulation bids for decreased production or increased consumption. The TSOs then use the bids in merit order to adjust power balance. Subsequently, an hour is defined either as an up-regulation hour or down-regulation hour. The highest up-regulation bid used becomes the sale price of balance power and the lowest down-regulation bid used becomes the purchase price, respectively. Otherwise the spot price will be used. (Fingrid 2004)

2.3.5 Financial Market

After the deregulation of the power market, market risks that had previously been latent showed up and there was an evident need for their management. Although bilateral agreements had been used before in the business to lock in prices, it seemed necessary to establish a transparent market place for power derivatives. The text here concentrates on the financial market of Nord Pool, as it also lays the ground for OTC-markets.

Nord Pool's financial market for forward contracts was established in 1993. The market initially used an auction trade system and agreements led to physical delivery. Traded contracts included base load, peak load and off-peak load contracts with a time horizon of up to six months. However, experience then showed that the concept needed to be modified, so as to encourage increased trading on the market. Auction trading was replaced by continuous trading, other than base-load contracts were removed from the list and trading was moved onto an electronic platform called PowerCLICK. Later, Nord Pool standardised the forwards to conform them to the OTC market. (Nord Pool 2004b, 4-5)

Nowadays all derivatives contracts at Nord Pool are settled in cash. The exchange currently quotes futures, forwards, options and swaps for regional price differences (Contract for Difference) with a time horizon of up to four years. The system price is used as the reference price for these derivatives contracts. Actually, theoretically the underlying of an option is a forward contract, since at maturity the buyer has the choice to enter into a forward contract. The fact that the contracts are settled in cash facilitates trading without regard to technical conditions whatsoever. (Nord Pool 2004b, 6-7)

Futures Contracts

A futures contract is an agreement to buy or sell an asset at a certain future time for a predetermined price. The buyer of the contract assumes a *long position* and agrees to buy the asset on a specified future date for a certain specified price. On the contrast, the other party assumes a *short position* agreeing to sell the asset. The price of the contract is called *delivery price* and the period, to which the price is applied, is termed as *delivery period*. The delivery price is calculated so that the cost of entering a futures contract is always zero. If we let K denote the delivery price and S_T the asset price at maturity, the payoff from a long position is $S_T - K$ and the payoff from a short position is $K - S_T$. (Hull 2000, 4)

The market seems to have a preference for short-term futures and long-term forwards (Nord Pool 2004b, 7). The reason lies in the way financial settlement is done for the different contracts. Both contracts require a margin account, which is normally pledged. However, financial settlement of a futures contract includes daily *mark-to-market settlement*, which means that the difference between the previous day's value and today's market value of the contract is credited to or debited from the buyers margin account. Of course, the opposite entry will show on the sellers account, although the exchange carries the counterparty risk. In contrast, no cash will flow in a forward agreement until maturity.

The fact that the margin account must have a balance within certain limits in accordance with contract size implies that margin calls are made from time to time, should the balance of the account decrease sufficiently. In other words, long-term futures contracts could tie up a substantial amount of capital and are therefore avoided. Furthermore, the time value of the cash flows affects the valuation of a futures contract, as compared with a forward. On the other hand, a futures position may be closed at any time without regard to settlement. Although the general understanding is that futures are standardised and forwards are traded exclusively on OTC-markets, both contract types are listed on Nord Pool and are standardised.

As of today, Nord Pool lists for trading only base load day and week futures contracts. There are eight consecutive weeks and six consecutive days quoted at all times. In addition to the daily mark-to-market settlement discussed above, a final spot settlement takes place during the delivery period. The *final settlement* covers the difference between the last closing price of the futures contract and the realised system price. (Nord Pool 2004b, 8)

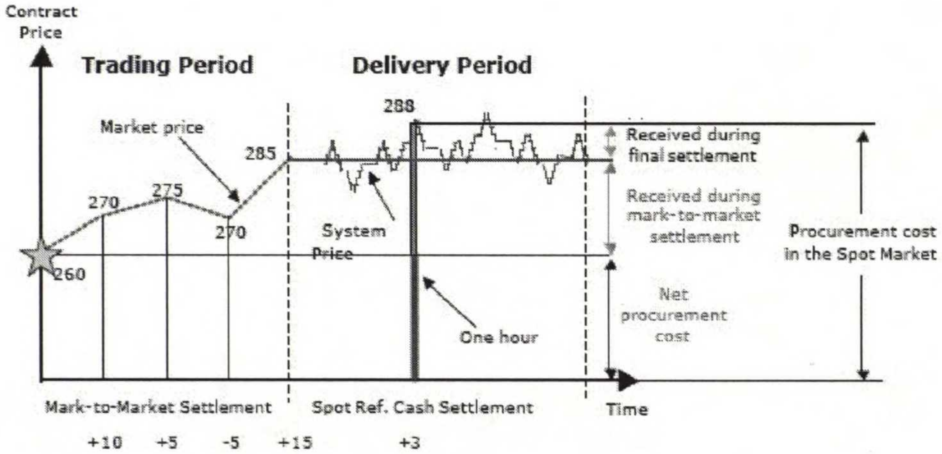


Figure 5: Futures contract settlement. Source: Nord Pool 2004b, 9.

Figure 5 above exemplifies the financial settlement of a futures contract. In the figure, a participant has entered a long position in a futures contract at the price of 260 NOK/MWh. During the trading period (mark-to-market settlement) the buyer receives the current market price less previous day's price. Then, for each hour of the delivery period, the buyer receives the difference between the prevailing spot price and the final closing price of the futures contract – in this case 285 NOK/MWh. The net effect is that, providing the participant buys physical power from the spot market, the total cost of physical procurement is equal to the hedging price of 260 NOK/MWh.

Forward Contracts

A forward contract is similar to a futures contract with the exceptions that were discussed above. The forward market is currently in a transition phase. New products will replace some of the old ones and the currency of all contracts will be the Euro from the beginning of 2006. Actually, all listed forward and futures contracts with delivery in 2006 or beyond are already denominated in Euros and are structured according to the new model. Forward contracts are traded in 1 MW blocks. (Nord Pool 2004b, 10-11)

As of today, there are four different forward products on Nord Pool's list: months, seasons, years and quarters. Table 2 shows the product structure as of July 2004. Year contracts are quoted for three following calendar years at a time. The denomination currency for the year 2005 is the Norwegian Krone (NOK) and the Euro beyond that. Year contracts will be split into seasons and into quarters after 2005. Splitting implies that the holder of a year contract will end up having three season contracts (or four quarters) as the year contract matures. Season contracts, in turn, are something that will be abolished by 2006. They are named Winter 1 (Jan-Apr), Summer (May-Sept) and Winter 2 (Oct-Dec) as they are meant to cover the respective seasons of the year. In contrast, quarter contracts cover the four three-month periods of a calendar year. Unlike seasons, quarters will be split further into months. Lastly, month contracts are listed on a 6-month continuous rolling basis and will not be split further at maturity. (Op. cit.)

	Product Series	Delivery Hours	First Trading Day	Last Trading Day	Start of Delivery Period	End of Delivery Period	Cascaded From	Currency
MONTHS	ENOMAUG-04	744	2.2.2004	30.7.2004	1.8.2004	31.8.2004		NOK
	ENOMSEP-04	720	1.3.2004	31.8.2004	1.9.2004	30.9.2004		NOK
	ENOMOCT-04	745	1.4.2004	30.9.2004	1.10.2004	31.10.2004		NOK
	ENOMNOV-04	720	3.5.2004	29.10.2004	1.11.2004	30.11.2004		NOK
	ENOMDEC-04	744	1.6.2004	30.11.2004	1.12.2004	31.12.2004		NOK
	ENOMJAN-05	744	1.6.2004	30.11.2004	1.12.2004	31.12.2004		NOK
SEASONS	FWV2-04	2 209	2.1.2002	30.9.2004	1.10.2004	31.12.2004	FWYR-04	NOK
	FWV1-05	2 879	2.1.2003	30.12.2004	1.1.2005	30.4.2005	FWYR-05	NOK
	FWSO-05	3 672	2.1.2003	29.4.2005	1.5.2005	30.9.2005	FWYR-05	NOK
	FWV2-05	2 209	2.1.2003	30.9.2005	1.10.2005	31.12.2005	FWYR-05	NOK
QUARTERS	ENOQ1-06	2 159	2.1.2004	30.12.2005	1.1.2006	31.3.2006	ENOYR-06	EUR
	ENOQ2-06	2 184	2.1.2004	31.3.2006	1.4.2006	30.6.2006	ENOYR-06	EUR
	ENOQ3-06	2 208	2.1.2004	30.6.2006	1.7.2006	30.9.2006	ENOYR-06	EUR
	ENOQ4-06	2 209	2.1.2004	29.9.2006	1.10.2006	31.12.2006	ENOYR-06	EUR
YEARS	FWYR-05	8 760	2.1.2002	28.12.2004	1.1.2005	31.12.2005		NOK
	ENOYR-06	8 760	2.1.2003	28.12.2005	1.1.2006	31.12.2006		EUR
	ENOYR-07	8 760	2.1.2004	27.12.2006	1.1.2007	31.12.2007		EUR

Table 2: Nord Pool forward products (July 2004).

Similarly to the trading of futures contracts, a sufficient cash balance is required from an exchange member engaged in forward trading. However, any settlement is postponed until the end of the trading period. (Op. cit.)

Contract for Difference (Swaps)

In section 2.3.5 the formation of area prices when there is insufficient interconnection capacity between price areas was explained. According to Nord Pool (2004b, 12), area prices in 2003 were equal only 27,5 % of the time. Furthermore, the reference price for financial contracts is usually the system price. Yet, physical procurement takes place in area prices. As a result, standard financial contracts, such as forwards or futures, do not give a perfect hedge against actual price changes. Nord Pool launched a *Contract for Difference* (CfD) to provide market players with a tool to manage this area price risk.

Physical procurement can now be hedged with a combination of, say, a forward contract and a CfD for the same volume and time period. The price differential, which eventually determines the cash flow of a CfD, is defined as the difference between the area price and system price. The price of a CfD thus reflects the market's expectations of the future price difference. The price of a CfD can be either positive, zero or negative. Figure 6 illustrates how the CfD works.

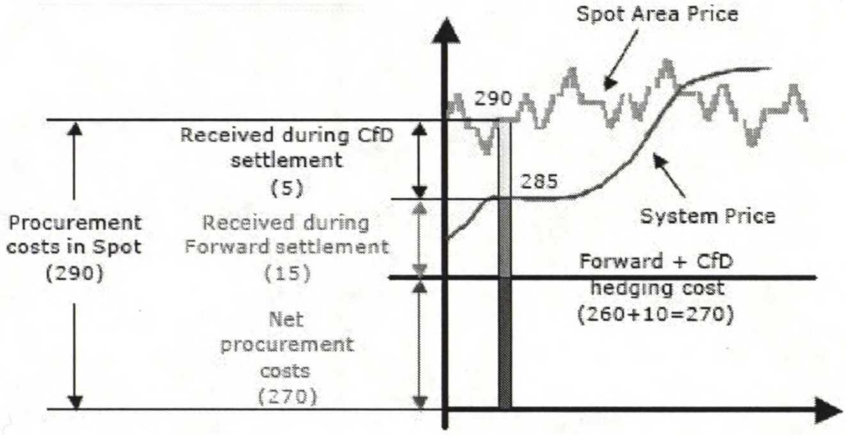


Figure 6: Hedging with forward + CfD. Source: Nord Pool 2004b, 13.

In the figure, a participant has entered a forward contract at 260 NOK/MWh and a CfD at 10 NOK/MWh. During the hour marked by the vertical column the participant receives 285 – 260 = 25 NOK from her forward position, which is settled against the system price. In addition, the participant has to pay – (290 – 285 – 10) = 5 NOK due to her CfD position, which is settled against the price difference between the area price and the system price. Altogether, the participant ends up paying 290 – 25 + 5 = 260 + 10 = 270 NOK for the delivery of one MWh.

Options

Since 1999, Nord Pool has offered European style options[3] for trade. The underlying commodity in the options offered by Nord Pool is either the seasonal (quarterly after 2005) or yearly forward contract (Nord Pool 2002, 7). Hull (2000, 6) defines a European option as follows. A European call option gives the right, but not the obligation, to buy the underlying commodity on a predefined date at a so-called strike price, which is determined beforehand. A European put option, then, gives the right, but not the obligation, to sell at strike. For these rights, the buyer of the option will have to pay a premium, or the price of the option.

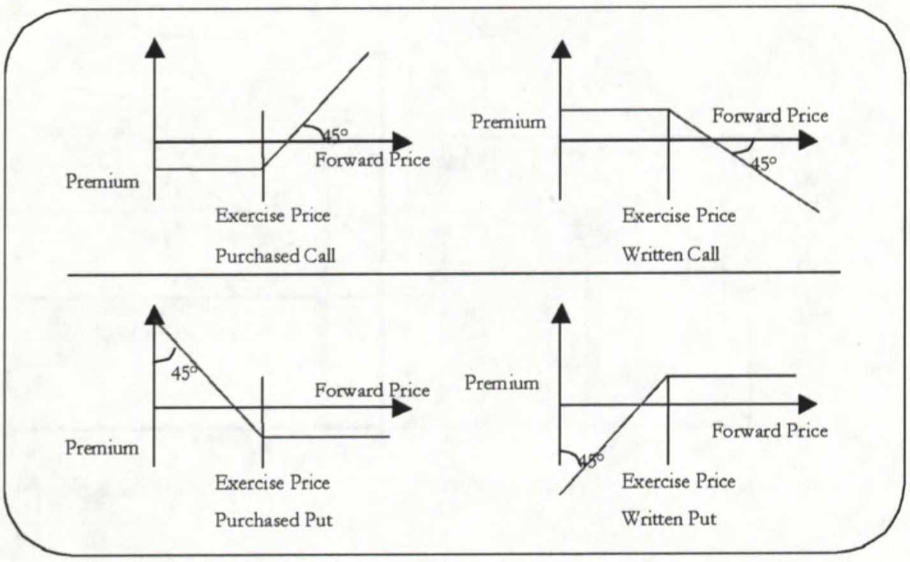


Figure 7: Payoff from an option position on the expiration date.

Essentially, the same price hedge as with futures or forwards can be achieved by options trading, but with options the downside risk is limited. Figure 7 illustrates the outcome of different option positions at maturity. Options are referred to as in-the-money, at-the-money or out-of-the-money. According to Hull (2000, 154), an in-the-money option has a positive intrinsic value, an out-of-the-money option has a negative intrinsic value and an at-the-money option has a zero intrinsic value, respectively. *Intrinsic value*, for its part, is defined as the maximum of zero and the value it would have if it were exercised

[3] A European style option can be exercised only on the expiration date. The opposite would be an American option, which can be exercised at any date during the option's lifetime (Hull 2000, 6).

immediately. Besides intrinsic value, an option has non-negative time value, which is the difference between the option's market price and intrinsic value. Finally, innumerable trading strategies can be employed by combining positions in options, futures or forwards and the underlying commodity in order to modify risk exposure and future cash flows.

2.3.6 Retail Market

This section is intended to give a short overview of the retail market in Finland alone, since the subject company of this study operates in Finland. For reasons that will become clear later, private consumption, as opposed to corporate consumption, is more relevant to this study and will therefore be granted the most attention.

Total electricity consumption in Finland amounted to roughly 81 TWh in 2002. Figure 8 shows the distribution of consumption in 2002. Of the over three million consumers in Finland almost 90 % are private households. However, their share of the volume is no more than 23 % or 18 TWh, whereas industrial usage is well over 44 TWh. The rest is consumed by agriculture, public administration and the service sector. Around 10 % of the total consumption is used for heating purposes. The amount of electrically heated households has increased from 481 000 in 1990 to 621 000 in 2003. (Adato Energia Oy 2003, 19-50)

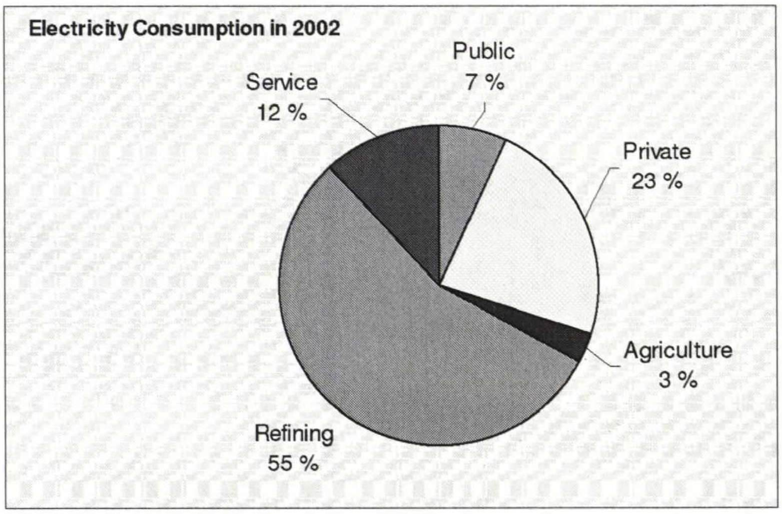


Figure 8: Electricity consumption by sector in 2002. Source: Adato Energia Oy 2003, 25

The Finnish consumers are serviced by 93 network owners and a few other traders. Yet, only seven companies have more than 100 000 customers and together they account for a half of the market (Adato Energia Oy, 36). Vattenfall Finland has approximately 350 000 customers and an annual sales volume of 5,6 TWh. Fortum is another large player with 400 000 customers in Finland. However, large industrial consumers typically own shares in production facilities and therefore acquire only a part of their energy from retailers.

One of the leading factors affecting electricity demand is temperature. The main reason is that, during wintertime, a large share of households and other buildings are heated electrically. However, unlike in some warmer countries, the relationship is not that strong in summertime. On the other hand, industrial consumption does have a much more limited dependence on temperature. For this reason, only private consumption and distribution losses will be included in the analysis later in this study.

Within each distribution network area, the dominant sales company has the obligation to deliver. This company must upkeep a public list of prices, a.k.a. *tariff prices*, which by the Electricity Market Act shall be reasonable to customers, i.e. correspond to the costs brought about by the customers. Although tariff prices can in theory be changed at any time, in practice they cannot be altered very often. Namely, customers have to be informed of the price change 30 days before it comes into effect. Also, competitive reasons may prevent retailers from increasing prices too much. Besides the continuous tariff contracts, most retailers offer fixed-term contracts at fixed-price to their customers.

Retail energy market was in theory completely liberated in the beginning of 1997, as the 500 kW limit was removed and all consumers became eligible to choose among suppliers. However, not until September 1998 when the *type-loading curve* practice was introduced was it possible for most private consumers to change supplier. Since the deregulation of the market, retail prices have come down slightly, but not as much as it first seemed, though. The actual reason for the price decline was an unusually good water reservoir situation around the turn of the millennium. Nonetheless, recent years have been very dry, which has naturally lifted the price curves. Figure 9 below exhibits how Vattenfall Finland's retail prices have developed during the last two years, as compared with market prices.

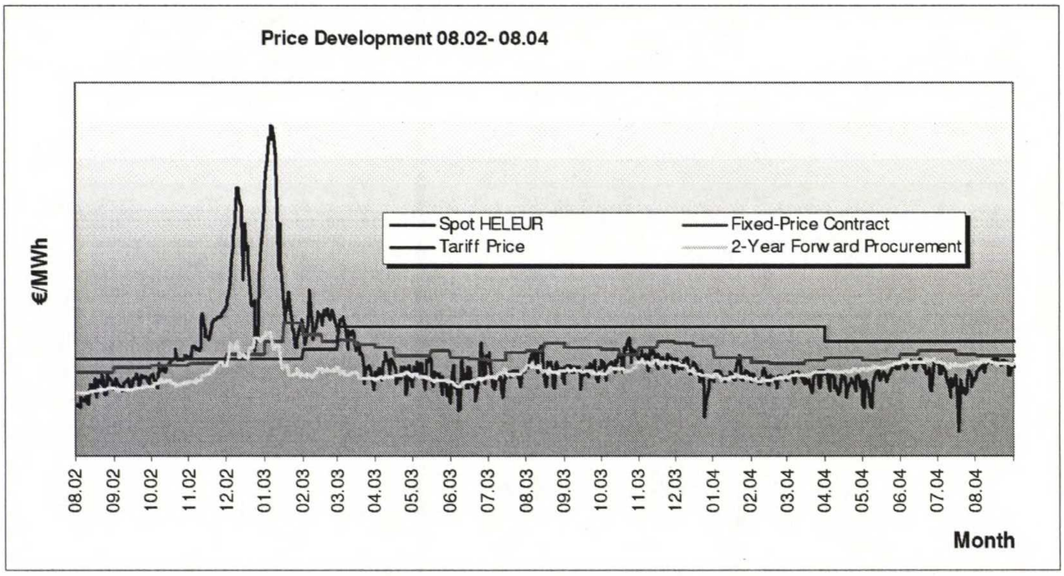


Figure 9: VF sales prices vs. market prices.

HELEUR denotes the area price of Finland. The forward procurement curve is based market quotes for forward contracts.

2.4 Risk Management

After the liberalisation of the market many electricity retailers have suffered significant losses, which in most cases can be attributed to insufficient risk management. In consequence, adequate risk management has become crucial to the business. This section deals with the retail business only. After an introduction to different risks, approaches to managing certain contract types and attitude to risk are discussed.

2.4.1 Types of Risk

There are a number of risks electricity retailers have to face, some of which are new to the industry since deregulation. The lot of them will be briefly gone through and then the text will concentrate on the most pronounced ones, namely the price and volume risk.

Counterparty risk or credit risk is defined as the uncertainty in the value of a (sales) portfolio due to the fact that all counterparties may not be able to meet their contractual obligations. Credit risk resulting from an individual counterparty can be measured through the probability of a default, counterparty exposure and recovery rate.

Counterparty exposure is the maximum amount that will be lost if the counterparty defaults. Recovery rate, in turn, is the proportion of receivables that can be expected to retrieve in such a case.

Currency risk originates from sales or trading in other than home currency. The value of a position in a foreign currency changes with the exchange rate, resulting in uncertainty about future cash flows in home currency. This risk can be managed fairly well e.g. with standard currency derivatives, although one problem is brought about the use of different currencies in spot purchases and financial settlement. As a result, the currency exposure is not fully known beforehand. This problem will vanish by 2006 when Nord Pool introduces the Euro for all its products.

Every company with expected future cash flows is exposed to interest rate risk. Changes in the term structure of the yield curve affect the present value of a cash flow stream and, consequently, can influence the valuation of a company. Interest rate exposure is not the most salient one for a state-owned energy retailer.

Operational risk should be a concern to every corporation. It is the risk of incurring financial damage because of shortcomings in the administration or internal control. Likewise, every business operates in some sort of a political and legal environment, so unpredictable changes in these can pose a risk to the business.

Price risk, as well as volume risk, is actually a many-faceted risk. Price risk is something that was latent prior to deregulation, as prices were fixed in periodical negotiations and were based on expected costs plus a mark-up. Producers are subject to price risk even if their production costs were fixed, since their future sales price is uncertain. On the other hand, consumers must tolerate fluctuation in their power expenditure, unless they choose to hedge their exposure through fixed-price contracts or portfolio management. Finally, retailers usually offer fixed-price contracts to their customers, which exposes them to variable profit margin.

Open position is herein referred to as the difference between hedged energy, which can be understood as procurement in advance, and expected sales volume. It is the very open position that is exposed to price risk. A long position implies that hedged volume exceeds expected sales volume and thus profits increase with the market price. On the contrary, a short position brings losses when the market price goes up.

In the end, price risk relates to the uncertainty about the balance between supply and demand. Since in a normal year more than 50 % of electricity in the Nordic market area is hydropower, water reservoir and precipitation levels have a major effect on the supply curve. Temperature, for its part, is the most important single factor behind demand. Other factors affecting supply and demand include power plant outages and market expectations. (See figure 1 under section 2.3.2)

Other risks that are closely related to price risk are price-area risk, balancing risk, liquidity risk and so-called profile risk. Price-area risk, which was discussed in section 2.3.5, is actually a form of basis risk. Basis risk arises from the possibility that the commodity to be hedged and the commodity underlying the hedge product do not completely match (Hull 2000, 36). Power in Sweden is not the same as power in Finland, at least in financial sense. In the absence of arbitrage[4] possibilities, spot price and futures price are the same at the expiration of the latter, provided no basis is present (for a proof refer to e.g. Hull 2000, Chapter 3).

Liquidity risk is relevant if there is a possibility that trading strategies cannot be executed due to inadequate liquidity on the market. Markets are said to be liquid when no individual transaction does move the market price, i.e. also larger trades can be realised at the prevailing market price. Balancing risk is actually a sort of volume risk. This risk materialises when short-term demand forecasts prove incomplete and additional costs owe to balancing power.

Also profile risk is a volume-related risk. Customers have a certain consumption profile, i.e. their consumption is not constant base load power, but varies from month to month and hour to hour. *Base load* is defined as invariable effect at all times, e.g. 100 MW. In

[4] Arbitrage is defined as follows: let $\mathbf{D} = \begin{bmatrix} -P_o \\ D_1 \end{bmatrix}$, where $\mathbf{D_1}$ is an n*m matrix of prices, where d_{ij} denotes the price of asset j in state i, and $\mathbf{P_0}$ is a 1xm vector of initial prices. Similarly, let x be a portfolio vector of dimension mx1. Then there is an arbitrage possibility if for some $\mathbf{x} > 0$, $\mathbf{Dx} \geq 0$ and $\mathbf{Dx} \neq 0$, that is, every component of $\mathbf{Dx}$ is non-negative but not identically zero. In other words, for a non-positive initial *cost*, there is a positive probability of gaining positive *profit* and zero probability of making losses.

contrast, weekday hours from 7 a.m. to 10 p.m. are referred to as *peak hours* and Sunday hours, as well as all night hours, are called *off-peak hours*. Moreover, also prices have a profile. The inverse demand function is an increasing function of demand, so the shape of the price profile conforms to that of the aggregate load. Consequently, peak hours tend to be more expensive than off-peak hours. Therefore, retailers are obliged to take account of the customer profile in pricing, i.e. to estimate the cost of uneven consumption. Now, profile risk is the risk that either price or load profile deviates from that expected causing variations in expected – and possibly hedged – cash flows. Figure 10 exhibits typical seasonal and intra-day load and price variations.

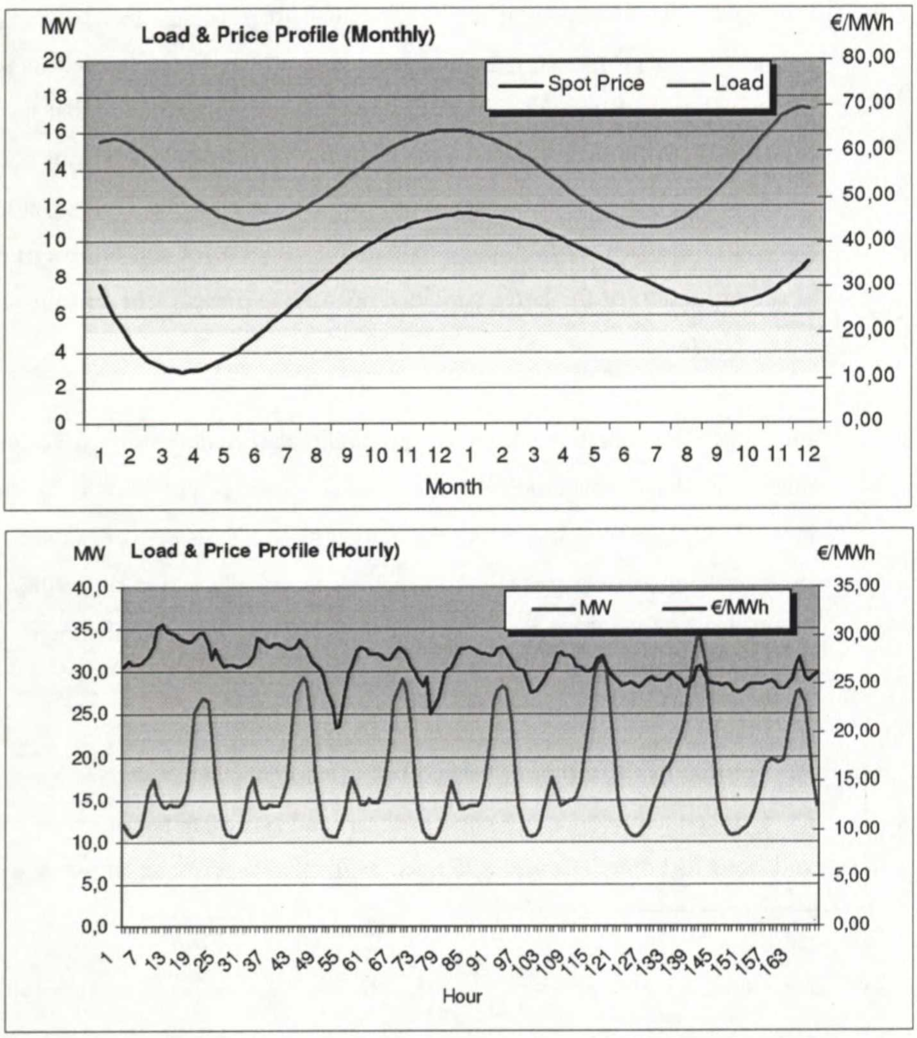


Figure 10: Load & price profiles.

Finally, the type of volumetric risk that will be in the centre of the next two chapters relates to contract structures and to the difficulty of accurately forecasting demand in a longer perspective. Corporate clients usually make available their expected consumption profiles and hedging, as well as pricing, is based on those. However, the outcome may be different and there is potential for losses if consumption exceeds expectations during expensive hours or falls short during cheap hours. Volumetric collars can be used to transfer part of the risk to the client (De Martini 2002). Nevertheless, volumetric risk is much more pronounced in the temperature-sensitive private consumption. Since prices and private consumption have a non-linear positive relationship, purchases to fill the gap between realised and expected volume frequently have to be made at skyrocketing prices.

Lastly, the new emissions trading mechanism and quotas add yet another uncertainty to the picture. Although the scale of its influence remains to be seen, it is certain that the scheme will lift the cost of fossil-fired production (Vattenfall AB 2003a, 26). As a result, the marginal cost curve will become steeper in the end, which implies that protection against extreme events, such as extremely cold winters, will gain more importance.

2.4.2 Contract Types and Hedging Strategies

Fixed Term Contracts

Fixed-term contracts are offered at a fixed-price to customers who do not like surprises in their electricity bills. The terms of the contract can slightly differ according to the size of the customer. Corporate clients are free to choose the period of their contract. The bigger the customer the less risk will be carried by the retailer but also the smaller are unit margins. While contracts are tailored to bigger clients, they are more or less standardised to smaller clients. Only two year-contracts are offered to household customers, partly because the legislation prohibits longer contracts . Pricing is based on (financial) market prices and the assumed consumption profile of the customers.

Hedging corporate contracts is fairly straightforward. Offers are given out as indicative and final prices are determined at the moment a deal is closed. The sales position adds up to the hedge portfolio and, providing the position is large enough, is immediately closed on the market. In this fashion, the retailer can lock in its profit margin. Of course, the retailer is still subject to most of the risks discussed in section 2.4.1.

However, managing the price risk inherent in private consumer contracts is somewhat trickier. In addition to forecasting the expected consumption of a customer, the supplier must be able to foresee the number of customers. Namely, the offers to these customers must reach them before their old contracts expire. For practical reasons the offer prices must be binding and the sales position must be aggregated for hedging purposes. Vattenfall's offers currently have a two-week validity, so the offers are sent out *at least* two weeks before the beginning of a potential contract. In addition, it is considered too risky to leave the position open until the offer period ends, so hedging must be carried out *at least* a month before the number of new contracts becomes clear. Of course corrections to the hedges can and will be made as forecasts become more accurate.

Although the number of contracts open in the future is not certain, it is the variability of consumption that is the most difficult to predict. Hedge volumes are usually based on normal year consumption patterns and can be revised in the light of new information. On one hand, too small hedge position is unwanted, since that would leave part of the sales position uncovered. On the other hand, excessively large position in derivative contracts increases the exposure itself, which is not desirable, either. While a futures or forward contract leaves the downside open, an option contract limits the potential loss to the paid premium. However, partially because of their relatively poor liquidity and high bid-ask spreads, standard option contracts may prove far too expensive to use at all, let alone speculative over-hedging.

Continuous (Tariff) Contracts

Tariff customers are usually those who have not very actively reflected upon their electricity contracts. As can be seen from figure 9, tariff contracts are consistently priced above fixed-price contracts in order to make the latter look more persuasive. However, even though tariff contracts are not very eagerly advertised, they are rather common amongst consumers. The popularity can probably be attributed to the fact that suppliers are required to upkeep a public price list with an obligation to deliver to those who have not reacted upon deregulation. Moreover, customers who do not renew their fixed-price contracts are automatically moved to tariff, given that they do not move to a competitor.

Price sensitivity with regard to changing supplier is slowly gaining popularity among private customers (Riski 2004, 2). As tariff customers are entitled to change supplier with two week's notice, it is difficult for a retailer to forecast future sales position. The direct consequence is that hedging becomes more complicated. Parameters to be decided include volume, time span and timing of hedging. Furthermore, there is a trade-off between the certainty of future procurement costs and the ability to offer competitive prices to customers. It seems sensible to carry out hedging in accordance with a pre-designed strategy that can be adjusted in the light of new information. Figure 11 shows an example of a hedging strategy where hedges are made more precise as delivery approaches.

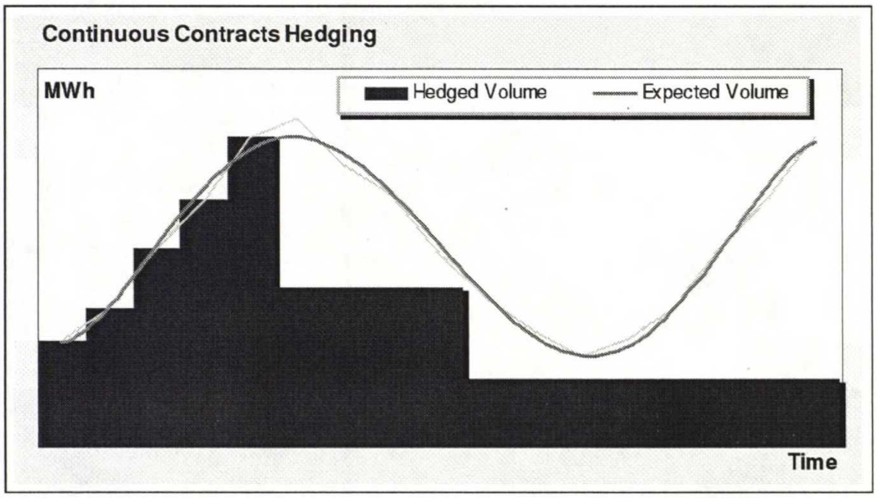


Figure 11: Hedging strategy for tariff sales.

Another consequence of increasing sensitivity to price among private consumers is that not all cost changes can be directly passed through to the consumer. This is highly in contrast with the past reality, where electric utilities where centrally coordinated and prices were cost driven (Vattenfall AB 2003a, 27).

2.4.3 Attitude Towards Risk

Risk management decisions are greatly affected by the company's attitude towards risk. Participants are usually divided into three categories according to their risk attitude: risk aversive, risk neutral and risk loving. Risk attitude, thus defined, reflects the participant's sensitivity to expected return, on one hand, and to the volatility of returns, on the other.

Risk aversive parties are willing to exchange a piece of the expected return to certainty, whereas risk lovers gain utility from the risk alone. Risk neutral parties are not interested in anything else than the expected return. (e.g. Luenberger 1997)

The case company of this study is a part of a multinational energy giant. According to the group's policies, each business unit is responsible for its own results and carries its own risks. However, active risk taking is not allowed for this particular business unit and so all financial transactions are made against its sales. A risk instruction stipulates the procedures for all exposures that cannot be hedged with certainty. The goal in risk management is finding a balance between risk and return. As a matter of fact, risk aversion is a dominant characteristic.

The risk attitude of the target company also motivates this study and will be considered when devising a means to tackle volumetric risk. Exposure to significant swings in cash flows is the main cause for concern.

3 THE WEATHER MARKET

Several solutions for weather risk management have already been developed. The first weather derivative, that is, a security whose value is determined by a climate factor, was dealt in the USA in 1997 and Chicago Mercantile Exchange (CME) began to trade temperature derivatives in 1999 (Shela 2000). Since those years the weather market has grown many-fold as measured by traded capital. The market has also matured in terms of product development. Along with new underlying factors, such as precipitation or wind speed, also structured products have emerged. These structures span weather-linked bonds, as well as tailor-made solutions mainly for the energy industry.

The growth of the global weather market has not been as painless and forceful as was foreseen in the beginning, though. HEX, the Helsinki securities and derivatives exchange, cancelled its weather contracts only a good year after they were launched in 2002 due to lack of interest. Also, the London International Financial Futures and Options Exchange (Liffe) stopped the quoting of European weather contracts following a sluggish demand. However, CME has enjoyed considerable success and has been expanding its geographical reach to Europe and Asia. (Lyon 2004a)

The Weather Risk Management Association (WRMA) reported in June 2004 that the total notional value of the global weather market was $4,6 billion from April 2003 to March 2004, which marked a 10 per cent increase from the previous year. CME's share of the market is remarkable, as more than 25 000 weather contracts worth over $580 million traded there during the first half of 2004. Despite the OTC market having diminished by 20 per cent, the market is believed to grow substantially in the near future. For instance, the New York and Tokyo exchanges are exploring the possibility of launching weather contracts. (Lyon 2004b)

Next, a few of the weather instruments that are commonplace on today's weather market are described and, subsequently, the pricing of them is touched.

3.1 Contract Types

3.1.1 Options and Swaps

Most weather contracts are tied to temperature development, measured by degree days, over a certain period. Basically, degree days are a popular proxy for energy consumption, as the correlation between degree days and power use can be as high as 97 per cent. A *degree day* is defined as the difference between a reference temperature, typically 65°F or 18°C, and the mean temperature for a given day. *Heating degree days* (HDDs) are calculated by subtracting the mean daily temperature from the reference temperature. *Cooling degree days* (CDDs), in turn, are calculated by subtracting the reference temperature from the mean temperature. No degree days are counted when the calculation would result in a negative value. HDDs are designed to measure the need for electrical heating during the heating season and CDDs for air conditioning, for instance, during the cooling season. (Clemmons et al. 1999)

There are basically three commonly traded contracts on the weather market: calls, puts and swaps. A long position in swap can also be seen as a bought call and a sold put with the same strikes. The strike value is then determined so that the values of the call and put are equal. The payout scheme of these contracts is such that the payment increases (or decreases) linearly with temperature. Alternatively, a fixed amount is paid in a binary payout scheme if the trigger value is reached. (Zeng 2000)

According to Zeng (2000), the parameters used to specify a generic weather derivative comprise:

- Contract type (swap, call or put)
- Contract period
- An official weather station from which the weather index is calculated
- Definition of the underlying weather index
- Strike value
- Tick size for a linear payout scheme or the size of a fixed payment for a binary payout scheme.
- Option premium.

The time span of a weather contract is usually one month or a specific season, e.g. winter, and it is always based on a single location or collection of locations. The latter is important, since a reliable index lays the ground for the contract settlement. *Tick size* is a multiplier used to convert the degree-day number into a pecuniary value. Also, due to the relative immaturity of the market, most contracts have a payout cap in order to boost liquidity. (Ramamurtie 1999)

The payout of a swap, call and put can be formulated as follows (Zeng 2000).

$$P_{swap} = k * (W - S)$$
$$P_{call} = k * \max(W - S, 0)$$
$$P_{put} = k * \max(S - W, 0)$$
$$k = \text{ tick size; W = weather index; S = strike}$$

Figure 12 exemplifies the payout from a long weather swap agreement. Tick size k determines the slope of the payout line and the payout is capped from above and below.

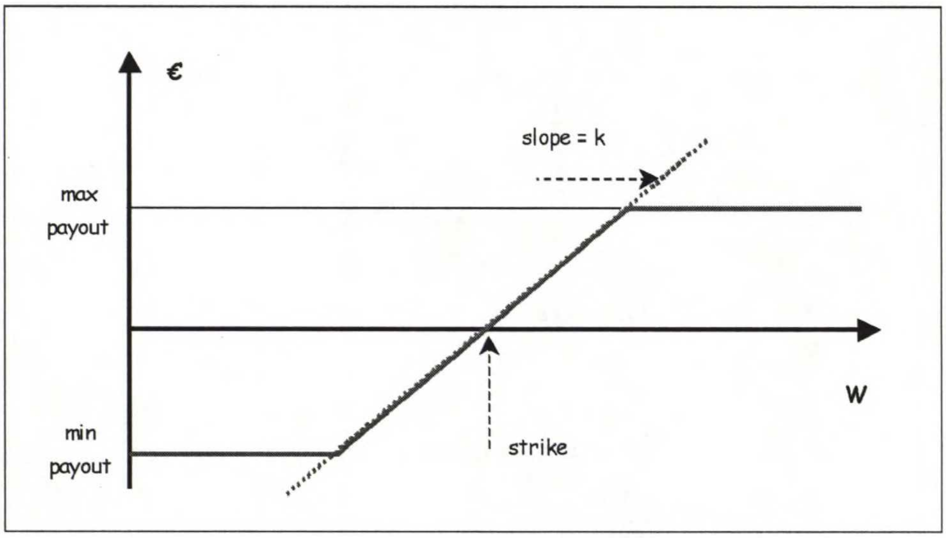


Figure 12: Payout from a long swap.

3.1.2 Weather-Linked Bonds

Weather assets do not correlate significantly with the economy and can thereby offer lucrative opportunities for capital market investors. They add to the diversity of multiasset portfolios, implying enhanced risk-return allocations. Coupled with the weather market's need for liquidity, these opportunities are likely to breathe life into the bond market with embedded weather options. (Dischel 2002)

The first temperature-linked note was issued in 1997 by Koch Energy Trading. Although this issuance was a success, the common understanding is that the development of the market is hindered by unnecessary complexity and difficulties in pricing. Also, weather is deemed as baffling by non-weather-exposed investors. (Op. cit.)

Weather-linked bonds are designed for mitigating non-catastrophic risks. The return on a weather-linked bond is pegged to a suitable meteorological index, such as average temperature or accumulated precipitation for an agreed period. The bond is characterised by an exposure period maturing at time $T' \leq T$. In addition, a trigger level for the index is defined. In case the trigger level K is not exceeded during the exposure period, the investor will receive the face value F at the maturity of the bond[5]. Nevertheless, if the trigger is crossed, the issuer of the bond is allowed to default on a part of the payment. In this case the investor only receives $(1-\alpha)*F$ where α denotes a so-called write-down coefficient. In exchange for this exposure, the investor can expect to receive higher return on the bond, i.e. the bond is priced cheaper, compared with a standard bond. (Briys 1999)

Dischel (2002) presents a few variations of the structure of a weather-linked note. The most conventional structures would include tranches that guarantee partial or full return of principal with coupons indexed to temperatures and others that guarantee the coupon, but the principal is indexed to temperatures. Dischel also has some noteworthy ideas for the structures of weather-linked notes. For instance, a 'volatile winter' note would have a positive yield in winters that are either warmer or cooler than average. As can be read from figure 13, such a bond would comprise both embedded call and put options on weather. Excess returns would be provided only if the winter fell sufficiently outside its normal range. Naturally, by leaving out the call option component, protection could be obtained solely for cold winters, which would lower the price of the note.

[5] Bonds are priced by discounting the cash flows on the bond to present time. A zero-coupon bond will always sell at a discount, since its face value is discounted to present time. In fact, the discount factor is equivalent to the yield on the bond. The coupon rate on a coupon-paying bond can be different from its yield. However, the yield on a bond that trades at face value is equal to its coupon rate. (Hull 2000, 88-90)

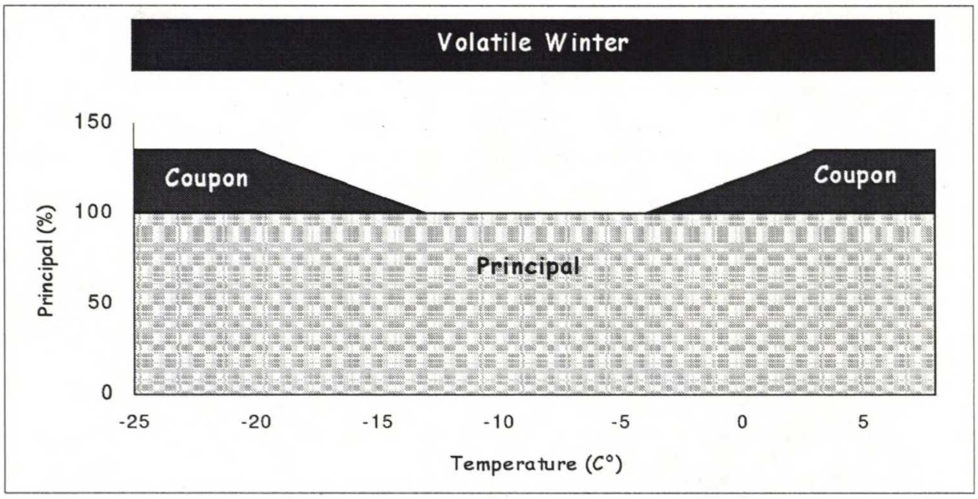


Figure 13: Weather-linked note (volatile winter). Source: Dischel (2002)

3.1.3 Structured Deals

Enron was one of the pioneers in the weather risk management business. Besides offering standard weather products, they carried out innovative structured deals. One of their insights was a so-called power demand swap. Its main idea was to provide a volumetric index, which could then be used instead of degree-days to make transactions on the market, hence eliminating the basis risk between actual and modelled consumption. (Hrgovcic 2001, 2)

While power demand swap is an example of a structured product, structured deals could be characterised as agreements tailored to the needs of a specific client. Lyon (2004c) reports on one such agreement bought by an Australian hydropower producer. The producer's operations are highly dependent upon rainfall levels and the firm is compensated under the agreement if annual amount of rainfall falls below a predefined level. For the protection, the buyer of the hedge will pay a premium plus an additional amount if rainfall levels prove to be favourable to it.

The hedge explained above is tailored to a specific company and therefore is not likely to be suited for other companies. This kind of structured deals have both positive and negative implications. On the positive side is that the agreement is capable of providing a nearly perfect hedge. However, there are two downsides to it that can immediately be thought of. First, since the hedge may not be useful to any other company, the agreement is doomed to have no liquidity on the market and once it has been written it will stay on the hedger's books until expiration. Second, because the risk is unique, the writer of the hedge will have difficulties in managing it completely and therefore has to demand a high risk premium to carry it.

3.1.4 Insurances

Weather-related insurances have a much longer history than weather derivatives do. Companies have long purchased insurance policies to take coverage from extreme weather phenomena, such as tornadoes or floods (Clemmons et al. 1999). Protection against catastrophic events is traditionally provided by insurance companies, but also Chicago Board of Trade launched catastrophe options in 1993 (Geman 1999). Moreover, it is not uncommon that insurance companies lay off a part of the substantial risk with so-called reinsurers (Ramamurtie 1999).

Insurances differ from derivatives in many important ways. First, a demonstration of loss and evidence of the link between this loss and the weather event defined in the policy are required (Geman 1999). Second, such conditions as attendant deductibles and extent of coverage are explicitly agreed upon (Ramamurtie 1999). Also, the payout from an insurance is based on the extent of coverage and loss that can be linked to a weather event, whereas the payout from a derivative contract usually grows linearly with a weather index, independent of how the weather actually affects the hedger (Alaton et al. 2002). Finally, insurances are priced differently from derivatives (Ramamurtie 1999).

Two aspects basically determine the availability weather-related insurances. The first is that those offering such protection must have a sufficiently large and diversified pool of insurable transactions to afford them adequate risk-adjusted return. However, it is frequently claimed that weather assets do not correlate with other type of assets and can therefore offer attractive investment opportunities as such. Secondly, the weather phenomenon must be easily measurable and transparent enough for binding contracts to be written. (Ramamurtie 1999)

3.2 Pricing of Weather Risk

Weather derivatives, being such a new invention, have not been very widely researched yet. Pricing seems to be so far the most studied aspect. Most pricing models for weather derivatives combine standard option pricing models with some type of actuarial prediction of weather conditions (Locke 1998). Yet, the application of standard pricing models from the financial world is not straightforward.

Robert Dischel (1998) argues that the prominent Black-Scholes framework does not work for weather derivatives for various reasons. First, the Black-Scholes model is based on an underlying tradable commodity, whereas in weather derivatives there is no such commodity. Secondly, weather derivatives are usually based on an accumulative value such as cumulative degree-days over some period – a feature similar to the averaging in Asian-style options (Dischel 1998). Yet, Sandor (1999) contends that the Black-Scholes model cannot be used to valuate path-dependent options on averages or cumulative indices. Namely, one of the assumptions behind the Black-Scholes model is that the underlying price process is geometric Brownian motion (GBM). However, the average of prices that themselves follow GBM does not usually satisfy this assumption. Lastly, as weather cannot be traded, it is impossible to fulfil the risk neutrality argument of the Black-Scholes framework (Sandor 1999).

Zeng (2000) discusses the applicability of actuarial method to pricing weather derivatives. The actuarial approach is based on the probability distribution of the contract payout. The breakeven value for long-term non-negative profits is equal to the sum of the expected value of the contract payout (μ) and overhead expenses (e), i.e. $E[C] = \mu + e$. Thus, the writer of an option must demand a premium greater than E[C] to remain profitable in the long term. The seller determines the risk premium according to its attitude risk and possibilities to diversify the risk. The exercise index of swap would be chosen so such that the expected net payout is zero.

Zeng (2000) also points out a few drawbacks of basing the valuation on purely historical data. Firstly, the size of a historical sample is frequently too small to allow a reliable estimation of the values at the tails of the distribution. Second, weather indices are known exhibit long-term variations, which makes the estimates sensitive to the number of years included in the historical data. It is then impossible to say whether such variations are persistent trends that should be modelled or movement with larger scales than the length of the history. Lastly, the writer remarks that most weather indices show strong autocorrelation, which reduces the reliability of the statistics. As a better alternative, Zeng proposes a Monte Carlo simulation approach, preferably one that takes account of current weather forecasts.

Also Dischel (1998) advocates the use of stochastic Monte Carlo simulations to value weather derivatives. The foundation of his approach is the model for temperature simulation. The fair value of a temperature-contingent derivative is straightforward after the distribution of temperatures is known. It suffices to calculate the average of the simulated payouts and discount them to the present.

Dischel (e.g 1999a; 1999c) stresses the important role of the weather data in the valuation. Opportunities exist, as different players take different views of history. Of particular concern is the length of the historical record. Dischel (1999) recognises three alternatives for the choice of record length. One either use all the data available, only the most recent history or something between the two extremes. The recent data is probably most representative of the current conditions, but is generally inadequate for reliable parameter estimation. On the other hand, using all the data hides potential climatic shifts that have taken place more recently. According to Gakos (1999), 20 years is the market practice, while Dischel recommends a record length of 30-50 years.

Dischel (1999c) proposes that the history be shaped to solve the conflicts between different record lengths. According to him, volatility should be estimated using all the available data., since every peace of information is valuable. However, averaging should be performed over the recent decades only, especially if the climate has changed due to urbanisation, for instance. History can then be reconstructed by removing the perceived trend by fitting a polynomial equation to the time series.

The pricing issue is argued to be a stumbling block to the development of a liquid and functioning weather market (Dischel 1999b). Although a potential end-user was able to construct an otherwise perfect hedge, finding the "right price" could turn out to be unexpectedly difficult. Even if the end-user had the appropriate tools to evaluate a fair price, the market quotes could be at quite different levels. Deviations from the fair price can be due to different approaches to pricing, which contributes to wide bid-ask spreads, or high liquidity premiums (Dischel 1999a). Also, argues Locke (1998), lack of standardised pricing of weather derivatives throughout the industry makes it hard to mark them to market.

4 ANALYSIS OF VOLUMETRIC RISK AND WEATHER DEPENDENCY

The relationships between temperature, load and prices make it possible to model the effect of temperature eventually on profits (Rookley 2000). Still, the non-linear nature of the strong correlation between spot prices and load complicates the analysis somewhat (op. cit.). As will be shown shortly, prices tend to rise more steeply when load is increased than they decrease when load is reduced. This can be interpreted so that the upside risk is more salient than the downside risk, which indicates that conventional volume-weighted hedges may not provide the desired protection, even on average.

Another problem is created by the difficulty of separating temperature-induced price risk from other types of price risk. Although the correlation between temperature and load is often as high as 90 %, prices may not correlate with temperature as strongly (Hrgovcic 2001, 2). Temperature affects demand through increased electrical heating and greater usage by process industries during cold times. However, the supply side may also be affected by such occurrences as unplanned outages or low water reservoir levels. To get a perfect hedge companies would have to take on both price coverage through electricity derivatives, for example, and volume coverage through weather derivatives (Richard Bernero in Locke 1998).

Attention will now be shifted to thoroughly defining and analysing the nature of volumetric risk and weather dependency in retail electricity business.

4.1 Definition of Volumetric Risk

Volumetric risk derives from the inability to accurately forecast future demand (e.g. De Martini 2002). Different types of volumetric risk have already been discussed in this study. However, from now on the focus will be aimed at a specific type of volumetric risk, i.e. temperature-induced volumetric risk, which will be both conceptually and quantitatively analysed.

As was explained in the introduction, the problem is that sales prices are fixed beforehand, whereas only the expected part of procurement can usually be hedged. As better knowledge arrives, the hedges can of course be adjusted, but at that point it is frequently far too late. The correlation structure causes spot prices to increase with load and vice versa. Moreover, unless the new information is company-specific, the forward market reacts accordingly. As a result, additional purchases to fill the gap between hedged and demanded energy must be made at prices higher than the sales price. On the other hand, if consumption falls short of expectations, the surplus energy (in financial sense) must be sold back to the market at a loss.

To get a more analytic picture of the risk, let us examine the procurement cost equation (4.1). The total procurement cost for a given time interval is equal to the product of (volume-weighted) price and volume. Price and volume are actually stochastic variables and can be further divided into a deterministic part (expected value) and deviation from the expected value, which is uncertain. Expansion of the product yields the three terms on the right-hand side of the equation. The first term is the product of actual demand and expected price. If we now take the forward price as the expected price and assume that customer price is set equal to the forward price, disregarding profit margin and administrative costs, this term is invoiced from the customer.

The second term, in turn, is the product of expected volume, which is known in advance, and the difference of realised price and expected price, which is now assumed to be equal to the forward price. But this price difference is then exactly equal to the payoff from a long forward position. Therefore, this term can be hedged with no cost, since the initial price of a forward contract is zero by definition. Consequently, it is the last term that the retailers are concerned about.

$$P * V = (E[P] + \Delta P) * (E[V] + \Delta V) = E[P](E[V] + \Delta V) + E[V]\Delta P + \boldsymbol{\Delta P \Delta V} \qquad (4.1)$$

$$\mathrm{P} = \mathrm{Price}\,;\ \mathrm{V} = \mathrm{Volume}$$
$$\Delta \mathrm{P} = \mathrm{P} - \mathrm{E[P]}\,;\ \Delta \mathrm{V} = \mathrm{V} - \mathrm{E[V]}$$

By definition, $E[\Delta P] = 0$ and $E[\Delta V] = 0$. Should the retailers then not be indifferent about the uncertainty, as the differences are expected to average out in the long-term?

There are two considerations that say the opposite. The first is related to the risk attitude of owners and investors. Namely, since most of us are risk aversive, we tend to prefer stable and predictable cash flows to highly variable. This is actually the reason why hedging is practised in the first place. Hedging has an advantageous effect on the cost of financing and usually increases shareholder value, as well. The other reason for not disregarding the last term in equation 4.1 is the fact that the *joint probability distribution* of the price deviation and the volume deviation may neither be symmetrical nor have an expected value at zero.

As a matter of fact, empirical evidence gives rise to a hypothesis that the change in price is steeper when load increases, as opposed to unexpectedly low demand. In mathematical terms, the joint distribution is skew to the right, i.e. the median is below the mean, which results in a positive expected value of the product of the deviations. Let us now assume that the income corresponding to the procurement in equation 4.1 is equal to the first two terms, i.e. customer invoicing and hedge result. Taking the expectation of the difference of positive and negative cash flows then yields $E[-\Delta P \Delta V]$. Hereafter, the negative sign will be dropped and positive value will be considered as cost.

Further elaboration gives the following equation.

$$\begin{aligned} E[\Delta P \Delta V] &= Cov(P,V) = E[PV] - E[P]E[V] \\ &= \left(\frac{E[PV]}{E[P]E[V]} - 1 \right) E[P]E[V] \end{aligned} \tag{4.2}$$

What equation 4.2 actually tells is the obvious fact that to move the expected cash flow to zero, one either needs a deterministic cash flow equal to the bias or a stochastic cash flow with the desired statistical property. However, the price of any derivative contract is the risk-adjusted discounted expected value of its payoff. Hence, the only perceivable way to fine-tune the expected cash flow upwards is to adjust customer pricing accordingly. The required increase is given by equation 4.2.

Even if the relationship between the deviations were linear, the expected value of their product would not be zero. On the contrary, only if the deviations were uncorrelated would this whole analysis be unnecessary. However, provided that deviations to both directions are as likely, a linear relationship would give a more balanced cash flow, leaving much less importance to additional hedging. Given that the expected value is difficult to move, the rest of this study is devoted to manipulating the shape of the distribution of cash flows.

Actually, a number of things can have an influence on the outcome of the term $\Delta P \Delta V$. Temperature can be singled out as the most important factor behind demand. Demand, in turn, is one of the main determinants of price. However, there are other important factors affecting price on the supply side, as well. These factors include fuel prices, precipitation levels, water reservoir levels and plant outages. Reservoir level seems to be the most salient one of these.

Nonetheless, this study will concentrate on the temperature-induced risk alone. It implies that the effect of temperature will have to be extracted from the joint effect of all factors. This is exactly what will be done in the next section. The risk related to hydrological situation is due to the fact that the expectations of future hydrological balance, which are inevitably reflected by the forward prices, may prove to be wrong and thereby cause spot prices to deviate from those expected. A study on hedging exposure to rainfall could be a natural continuation of this thesis.

4.2 Quantification of the Exposure to Temperature

4.2.1 The Model and Methodology

As was remarked above, the primary intention here is to model the effect of temperature fluctuations on the performance of the case company. It thereby seems quite natural to use temperature as an input in the model. An econometric model for the uncertainty, i.e. the term $\Delta P \Delta V$, will be developed. Customer load will be modelled with a linear *ordinary least squares* (OLS) method and non-linear OLS will be used to capture spot price development. In the end, the model will be completed with a dose of stochastic variation.

Temperature is the main determinant of customer load, so that will be used as an explanatory variable in the first model. However, there are other factors behind demand, as well, which are more or less predictable. To capture these other effects a dummy variable for months, weekends and years will be added. The year dummies, and to certain extent the month dummies, explain the changes in customer base, which can be quite substantial. Moreover, weekend consumption behaviour differs from weekdays. Finally, a dummy will be added to steepen the demand curve when temperature falls below –20 centigrades. *Dummy variables* are used in a regression equation to measure the effect of a qualitative factor. According to Dougherty (1999), dummy variables have the two important advantages of providing a way to test whether the qualitative factor is significant and making the regression estimates more efficient.

Load data has been obtained as follows. The starting point is delivery data from the grid area where Vattenfall Sales has an obligation to deliver. Deliveries by other sales companies within that grid area are then deducted. To the remaining volume is then added the sales of Vattenfall within external grid areas. The result is the total delivery by Vattenfall Sales. However, as corporate consumption is far from being as responsive to temperature variations as household consumption, I have decided to leave out all hourly-metered premises. Consequently, the load that I have chosen to examine here includes private consumption, distribution losses, as well as some municipal and corporate premises whose main fuse size does not exceed 3x63 ampere or who have chosen not to call for tenders from the suppliers.

Modelling the spot price is slightly more difficult. The most direct way would be to use the system load as the primary explanatory variable. Yet, appropriate load data is rather difficult to obtain and the data referred to above has properties that make it an unreliable determinant of prices. First, the data is specific to Vattenfall Sales and is not fully representative of the system load. Second, the data includes the influence of such exogenous variables, e.g. changes in the customer base, that do not affect the system load and thereby prices.

The exogenous variables cause a strong trend in the load data. However, de-trending is out of the question, since there is currently no way of telling to which extent the trend is caused by factors that actually should be included. Hence, I have decided to take the indirect approach and model prices through temperature variations. This is not far-fetched, given that temperature alone explains well over 90 per cent of the variance of load.

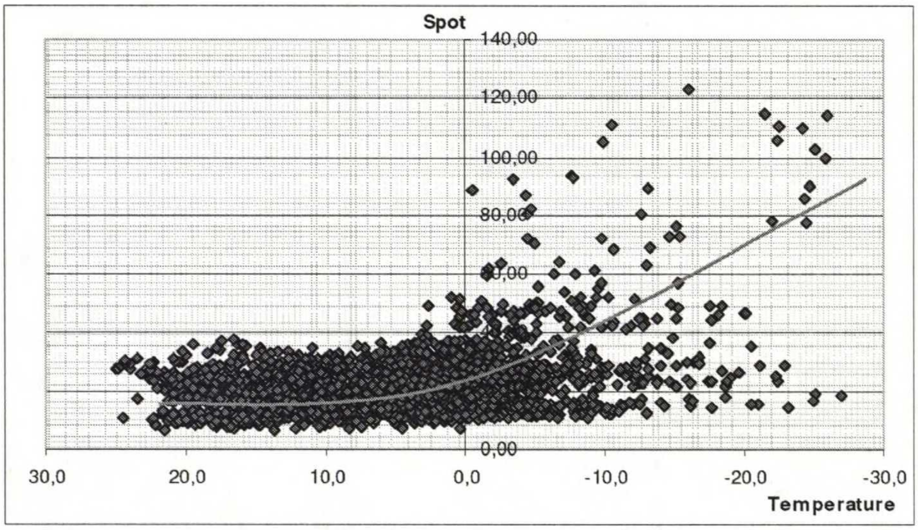


Figure 14: Relationship between temperature and prices.

Figure 14 above shows the non-linear nature of the relationship between temperature and spot prices. Regression runs reveal that an exponential function gives the best fit, keeping in mind that one cannot make direct comparisons of R^2 between models employing different functional forms (Dougherty 2002, Ch. 5). In consequence, logarithmic transformation of the dependent variable will be used. Similarly to the load model, dummy variables will be used to capture the effects of different months and years. Explanation to the significance of those dummies most likely resides in changing supply conditions. Additionally, two slope dummies are added to steepen the curve as temperature falls below –15 and –20 centigrades, respectively.

However, the model for spot is not complete yet. Supply conditions are not explicitly represented in the equation. Also, it was pointed out that the effect of temperature needs to be separated from the joint effect of all explanatory variables. Therefore, *reservoir surplus* – the difference between actual reservoir level and median level – is added to represent supply conditions. This is justified by figure 15, which exhibits a Pearson correlation of 0,76 between spot price and reservoir surplus. An even better variable would be the hydrological balance, which includes rain forecasts, snow and ground water.

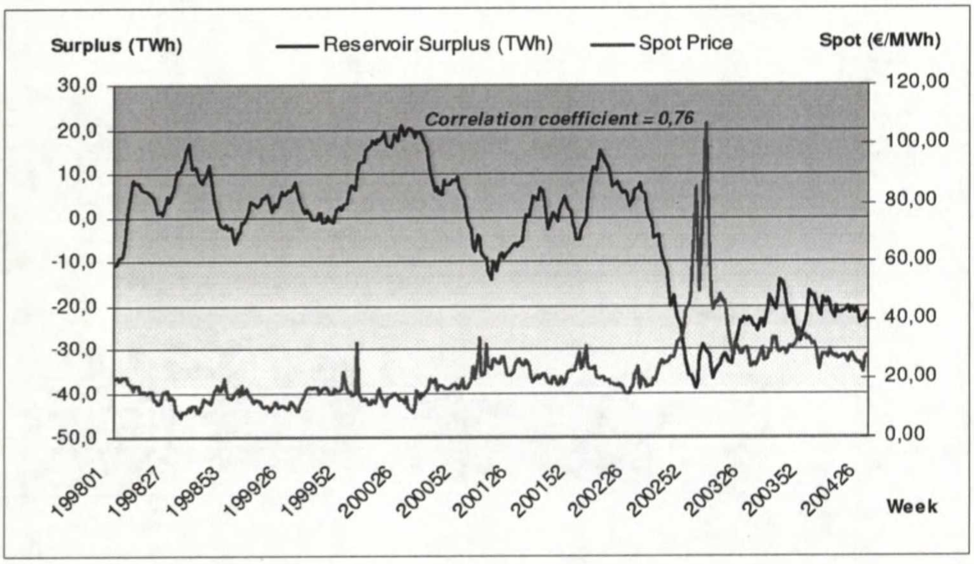


Figure 15: Relationship between reservoir level and spot price.

After the estimation of model coefficients, the expected spot price and load can be evaluated. Expected load is determined by setting the temperature of each day equal to the so-called normal temperature for that day, i.e. the historic average over a long period of time. The temperature data at my disposal is retrieved from the official weather station in Tampere, Finland, and covers the period 1979-2004. Due to the relative shortness of the data period, temperatures do not show any sign of a strong trend. Moreover, Jewson & Spencer (2004) argue that the existence of a trend does not automatically mean it should be removed, since there is a severe danger of overfitting.

Actually, this way one recovers the normal load and not necessarily the unbiased expectation of the load as is shown by the Jensen's inequality for convex functions (Dudewicz & Mishra 1988, 298): $f(E[x]) \leq E[f(x)]$. However, for practical purposes this is at least as good as any other estimator.

Expected, or normal, spot price is then determined equivalently with the exception that also reservoir surplus for each day is set equal to its long term average, i.e. zero. In reality, the expectation is dependent on the expected reservoir levels, but here I expressly wanted to exclude other effects. Correspondingly, when the expectation is evaluated against the realised spot, the effect of reservoir levels must be removed from that, too. Additionally, when spot prices are simulated the reservoir surplus can be retained at zero level.

Subsequently, the historic outcome of the term $\Delta P \Delta V$ can be evaluated by calculating the deviations from the expected price and volume for each day. In this manner, the historic distribution of temperature-inflicted losses is discovered. By ordering the resulting series by temperature, or alternatively by load, a loss curve can be drawn, which will give an idea of the shape and slope of the loss function.

Finally, the last step is to simulate the marginal effect of temperature. For this, load and prices need to be simulated and compared with normal values. Load is simulated by increasing the temperature deviation one degree at a time and evaluating the model presented above. Because the residuals of the model are normally distributed a normally distributed stochastic element is added to each load estimate. The model is thus a hybrid with temperature as the primary risk factor.

Spot price, without regard to reservoir levels, is simulated likewise only with a few modifications. Namely, the residuals of the spot model are indeed very close to normally distributed, but they exhibit relatively strong serial correlation. In other words, supply and demand shocks do not dissipate immediately, but last often a day or two after the shock. Consequently, a correlation structure will be implemented to the simulated error terms. Additionally, although the error term has a lognormal distribution, it does not seem capable of generating the jumps that temperature shocks do in reality. So, a uniformly distributed jump process will also be added to the simulated model.

The details and results of the described model are explained next.

4.2.2 Relationship Between Temperature and Load

The regression equation for load takes the following form.

$$L = \alpha + \beta_1 T + \sum_{i=2}^{12} \beta_i M_{i-1} + \sum_{i=13}^{14} \beta_i Y_{i+1990} + \beta_{15} Sat + \beta_{16} Sun + \beta_{17} Z + \varepsilon \tag{4.3}$$

L = Load; α = Model constant;

β_i = Model coefficient; ε = Residual;

$$T = \text{Temperature};\quad M_i = \begin{cases} 1 \text{ for month i} \\ 0 \text{ otherwise} \end{cases};$$

$$Y_i = \begin{cases} 1 \text{ for year i} \\ 0 \text{ otherwise} \end{cases};\quad Sat = \begin{cases} 1 \text{ for saturday} \\ 0 \text{ otherwise} \end{cases};$$

$$Sun = \begin{cases} 1 \text{ for sunday} \\ 0 \text{ otherwise} \end{cases};\quad Z = \begin{cases} 1 \text{ for } T < -20 \\ 0 \text{ otherwise} \end{cases};$$

Full results of the regression are given in appendix 1. The model fit is nearly perfect. The R *squared*, which measures the proportion of variance explained by the regression equation is as high as 0,973. Should the R squared measure have been small, there would have been a question whether it was positive only by matter of chance. Fortunately, this can be tested by means of an *F* test. *F* statistic for the goodness of fit is structured as follows (Dougherty 2002, Ch. 3):

$$F = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{R^2/(k-1)}{(R^2-1)/(n-k)}$$

Here ESS is the explained sum of squares, RSS stands for residual sum of squares, k is the number of parameters in the regression equation and n is the size of the sample. The *F* statistic gets a value of 1795, which means that the null hypothesis of no explanatory power is rejected at 0,1 per cent level.

Dougherty (2002, Ch. 4) maintains that adding a variable to a regression equation can never decrease the R squared and will generally increase it. This raises a question whether all of the variables genuinely belong to the equation. An *F* test can be used to test whether the inclusion of a certain variable significantly improves the fit. However, it can be shown that the t test of the coefficient of a variable is a test of its marginal explanatory power, after all the other variables have been included. Hence, it will suffice to look at the t statistics. The regression results reveal that all the variables included are significant at 0,1 per cent level.

Two properties are often considered above others when assessing the relevance of a model, namely *unbiasedness* and *efficiency*. An estimator is said to be unbiased if it produces the true value of a given parameter on average, i.e. its expected value is equal to the true value. Efficiency, in turn, is measured by the standard error of the estimator. The higher the standard error, the less accurate will a sample estimate be. Furthermore, providing the model residuals satisfy the so-called Gauss-Markov conditions, it can be shown that OLS regression gives the best possible results. However, not satisfying these conditions is likely to cause biasedness and/or inefficiency in the estimators. Next, the results are briefly examined from this perspective. (Dougherty 2002, Ch. 3)

Biasedness of a model can be detected from the non-zero expectation of the residual term. Biasedness can arise from model misspecification, for instance. According to Dougherty (2002, Ch. 7), leaving out a variable that belongs to the model generally makes the regression estimates biased and the standard errors, as well as the t tests, invalid. On the other hand, including a variable that does not belong to the model generally leaves the coefficients unbiased, although often inefficient. Hence, it would appear more reasonable to include a variable if one is not sure whether it belongs to the model, while controlling for needlessly large standard errors. Measurement errors can be another source of biasedness. Nonetheless, the mean of residuals of the model under scrutiny is zero, which gives a reason to believe that biasedness is not a problem.

Some of the possible causes of inefficiency are discussed next. *Multicollinearity* is a common problem in time series analysis and is caused by the combination of high correlation between two or more explanatory variables and one or more of the other variables being unhelpful (Dougherty 2002, Ch. 4). The higher the correlation between the explanatory variables, the larger are the variances of their coefficients, implying a greater probability of getting unreliable estimates. Multicollinearity can be suspected when the F statistic is high, but standard errors are large and, consequently, the t statistics low.

Dougherty proposes several remedies for this problem, but since the results do not show any sign of it, they will not be gone through here.

Two more phenomena deserve our attention, namely *heteroscedasticity* and *serial correlation* (a.k.a. autoregression). Heteroscedasticity relates to the variance of the model residual. One of the Gauss-Markov assumptions is that the variance of the residual is constant. However, in reality the distribution of the residuals may change with the explanatory variables. The problem can be significant, since it makes the estimators inefficient and invalidates the standard errors so that the t statistics will be overestimated (Dougherty 2002, Ch. 8). Figure 16 below shows the relationship between load and temperature. Although one generally should not make inferences based solely on visuals, heteroscedasticity does not seem to be a particularly severe issue in this case. In contrast, it can be deemed from figure 14 that the model for spot price will be subject to heteroscedasticity. Yet, as is also demonstrated by Dougherty, the logarithmic transformation probably alleviates the issue somewhat.

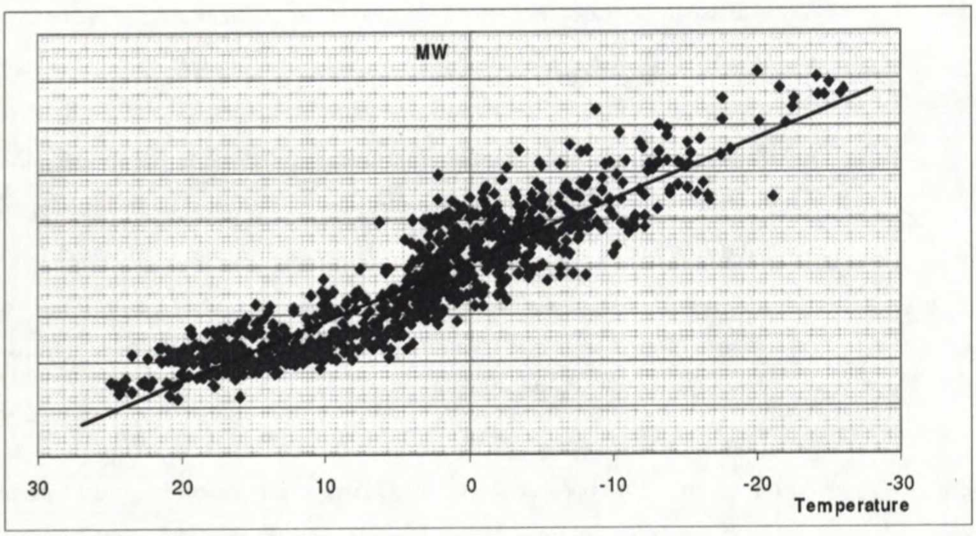


Figure 16: Relationship between load and temperature.

Finally, autocorrelation means that the residuals are correlated between themselves. Dougherty (2002, Ch. 13) maintains that the consequences are rather similar to those of heteroscedasticity. The coefficients stay unbiased, but the model is inefficient and the standard errors are wrongly estimated. Dougherty points his finger at the persistence of the effects of excluded variables as the most likely cause of serial correlation. One would not expect the problem to show up in the load regression, but leaving out an explanatory variable, such as fuel price, from the spot model is a potential cause of autoregression, since events rarely dissipate in one day.

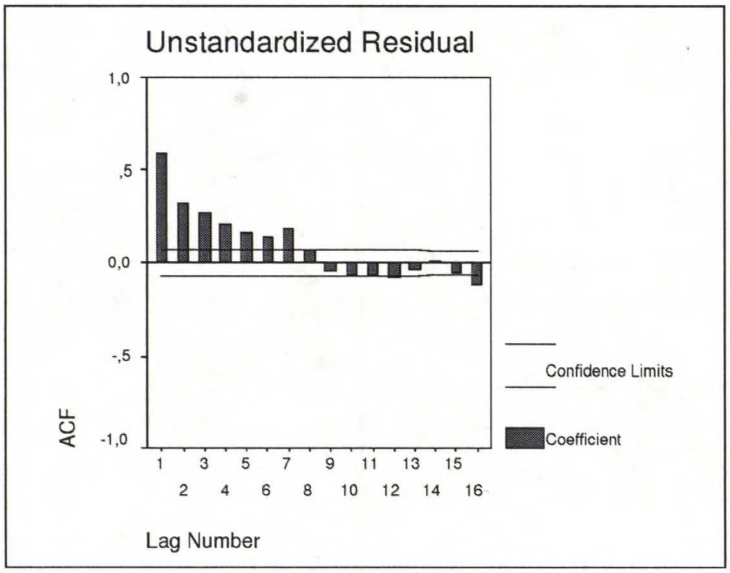


Figure 17: Autocorrelation of load residuals.

However, as can be seen from figure 17, my presupposition proves to be wrong. The first order autocorrelation appears to be quite strong, whereas the higher order correlations are more of a consequence of this. In other words, the model is not perfect. Rather, it seems to capture well the overall relationship between load and temperature, but fails to recognise the micro-level effects. Moreover, the marginal effect of temperature is high in winter months, but almost insignificant during the summer. Yet, the scarcity of data does not allow for providing such details accurately. I will not try to remove serial correlation from the model.

Also normality of the model residuals is a desirable result. The fact that standardised residuals follow a normal distribution makes it possible to model the error term as noise. On the other hand, the zero mean of the unstandardised residuals verifies the unbiasedness of the estimates. The normality of the residuals have been assessed in three ways. First, the histogram and P-P plot of the standardised residuals were examined (see figure 18). *P-P plot* compares the observed cumulative probability to that expected from a normal distribution. For a normal distribution they should be equal and the plot should be a straight line. Next, a one sample *Kolmogorov-Smirnov* (K-S) test was performed to the residuals. K-S test compares the empirical cumulative distribution function with the hypothesised distribution (e.g. normal distribution) and considers their maximum vertical distance as the test statistic (Dudewicz & Mishra 1988, 670-671). The null hypothesis is then rejected if the distance is larger than a critical value, which is derived from a certain theorem (cf., op. cit.).

According to the K-S test, the normality of the model residuals cannot be rejected at usual confidence levels. Also the histogram and P-P plot in figure 18 confirm their normality visually. Figure 19 exhibits the in-the-sample modelled load versus true load.

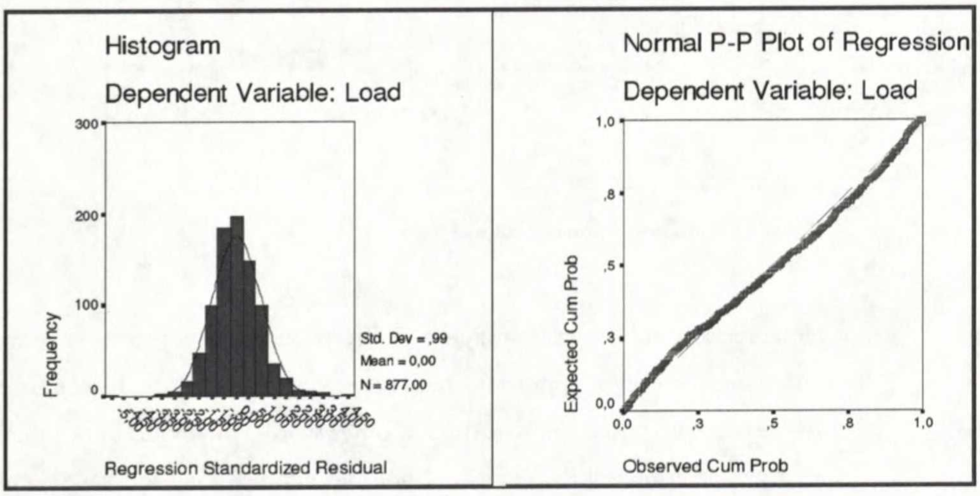


Figure 18: Normality of model residuals (load).

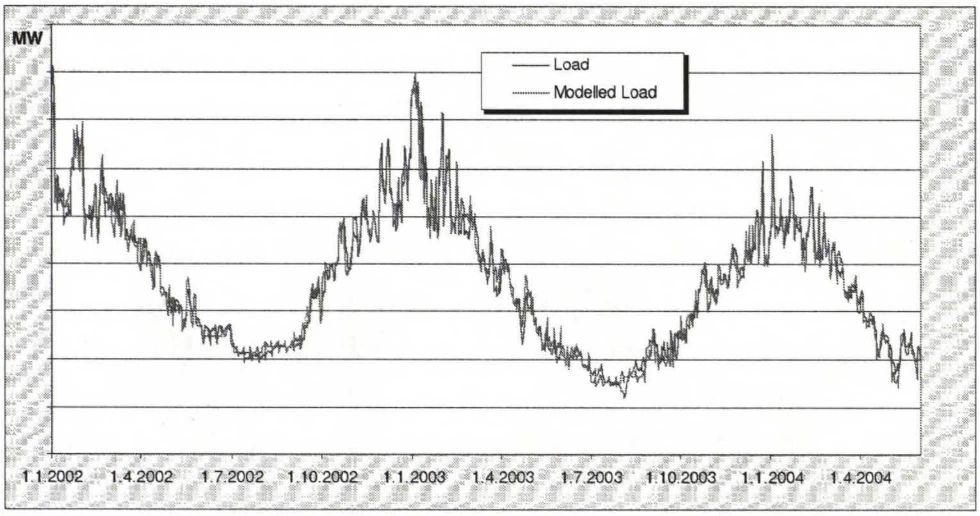


Figure 19: Modelled vs. true load.

4.2.3 The Model for Spot Prices

As was commented earlier, the spot model is far trickier than the load model. However, a simplified approach has been taken here and the results prove to be quite impressive. The regression model takes the following form.

$$\begin{aligned} Log(P) = \alpha + \beta_1 T + \beta_2 R + \sum_{i=3}^{13} \beta_i M_{i-2} + \sum_{i=14}^{18} \beta_i Y_{i+1986} \\ + \beta_{19} Sat + \beta_{20} Sun + \beta_{21} ZT + \beta_{22} YT + \varepsilon \end{aligned} \tag{4.4}$$

P = Spot price; α = Model constant;

β_i = Model coefficient; ε = Residual;

T = Temperature; R = Reservoir surplus

$$M_i = \begin{cases} 1 \text{ for month i} \\ 0 \text{ otherwise} \end{cases}; \quad Y_i = \begin{cases} 1 \text{ for year i} \\ 0 \text{ otherwise} \end{cases};$$

$$Sat = \begin{cases} 1 \text{ for saturday} \\ 0 \text{ otherwise} \end{cases}; \quad Sun = \begin{cases} 1 \text{ for sunday} \\ 0 \text{ otherwise} \end{cases};$$

$$Z = \begin{cases} 1 \text{ for } T < -15 \\ 0 \text{ otherwise} \end{cases}; \quad Y = \begin{cases} 1 \text{ for } T < -20 \\ 0 \text{ otherwise} \end{cases}$$

Similarly to the load model, temperature has a cut-off point at plus 15 centigrades, i.e. all temperatures above 15 degrees are assigned the cut-off value. This improves the fit, since temperature loses it explanatory power around that level. Reservoir surplus, in turn, is measured as the difference between actual and median reservoir levels in energy (TWh) and its value changes weekly. ZT and YT are so-called slope dummies that steepen the price curve at lower temperatures. This arises from the fact that marginal supply curve steepens as load draws closer to capacity limits, i.e. as temperature decreases significantly.

Full regression results are presented in appendix 2 and will be summarized next. Although the model in general is not as accurate as that for load, it explains as much as 86,6 per cent of the variance of the dependent variable. The *F* statistic is also high enough to remove any reservations about the significance of the R squared. Nevertheless, not all explanatory variables were significant in this regression. Namely, dummies for September, October and November can be rejected at 5 per cent level when December is used as the reference month (a.k.a. omitted category).

Some potentially significant factors are excluded from the model. Some of them, e.g. fuel prices or outages, are left out for the simple reason that no data on those factors were available. On the other hand, others, such as market psychology, are not directly measurable. Yet, the year and month dummies may compensate for their missing somewhat. All in all, the omission of certain variables can cause biasedness in the estimates and invalidate the test statistics. Hence, the results must be interpreted with caution.

Multicollinearity does not seem to be a particular problem in this regression, either, as interpreted from the standard errors, *t* statistics or the explanatory power of the model. However, heteroscedasticity can be suspected, given the high dispersion of the observations in the cold end of figure 14. The consequences of this property were discussed in the previous section. Since this is not primarily an econometric study, I will not try to apply any other correction methods besides using logarithmic transformation of the explained variable. Nonetheless, it is important to keep these drawbacks in mind when evaluating the relevance of the model.

Furthermore, the model residuals seem to suffer from some degree of autocorrelation. As was the case with load residuals, the first order autocorrelations seem to be relatively high, whereas higher order correlations are a consequence of this. Here, it is evident that the autocorrelation is caused by the persistence of the effects of excluded variables. Figure 20 shows the serial correlations up to 16 days' lag.

Lastly, tests on the normality of the residuals were performed. The mean of the unstandardised residuals is zero, as it should be. Also, deeming from figure 21, the residuals seem to follow the Gaussian distribution quite closely. However, the third quartile is somewhat underrepresented in the observed distribution. It appears that the normality hypothesis is rejected at 0,1 per cent level in the one-sample K-S test. Actually, a closer examination reveals that the residuals follow a logistic distribution with location zero and scale of approximately 0,09 (see e.g. Weisstein s.a. for a definition). This is confirmed by a two-sample K-S test, where the test distribution is a simulated sample from a logistic distribution with the desired parameter values.

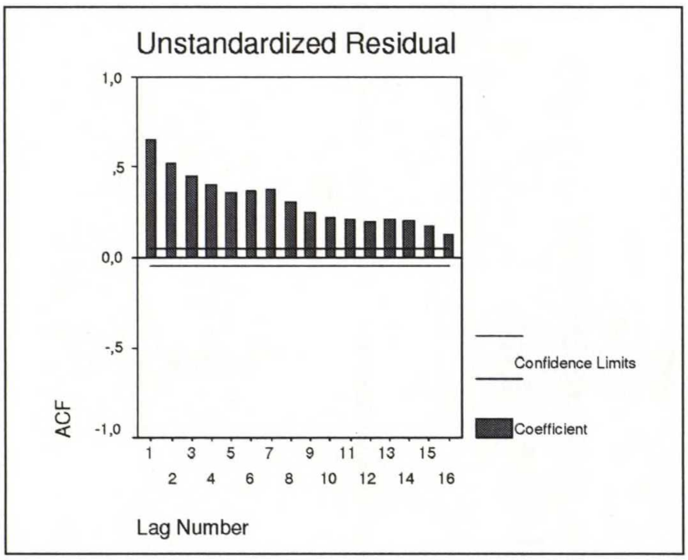


Figure 20: Autocorrelation of spot residuals.

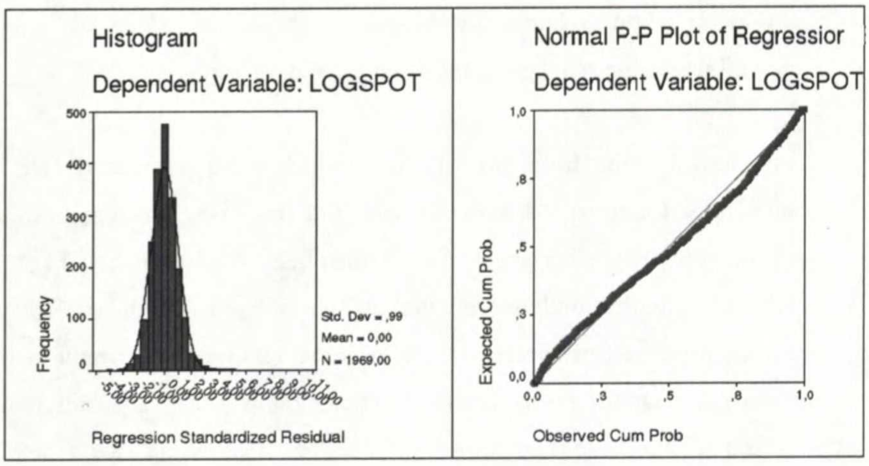


Figure 21: Histogram and P-P plot of spot residuals.

Figure 22 presents the in-the-sample comparison of the modelled spot series with the true series. It is evident that the dummy variables correct the level for each month and year on average, but the model seems to capture relatively well the price movements otherwise, too.

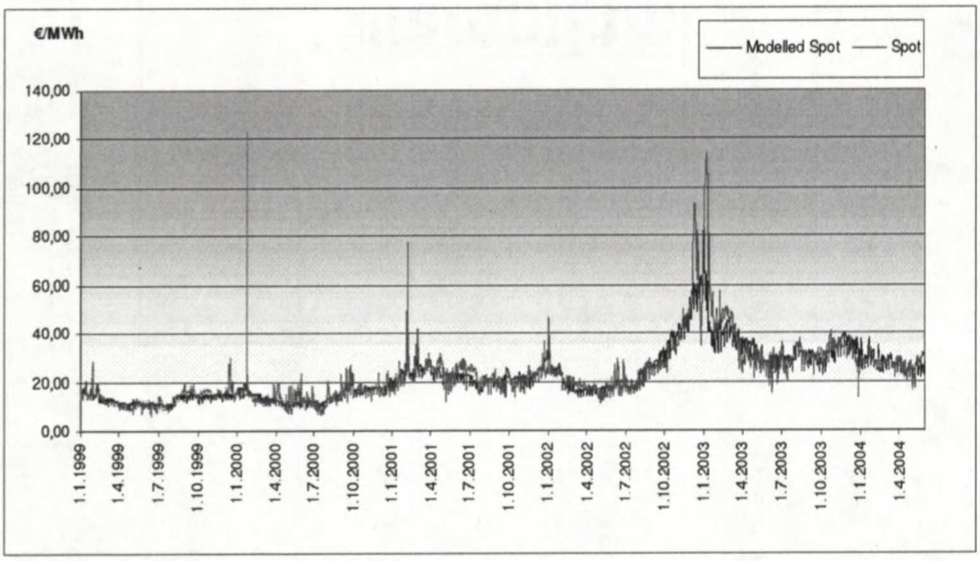


Figure 22: Modelled spot vs. true spot.

4.2.4 Limitations of the Model

So far, a regression model has been developed to explain load with temperature and spot prices with temperature and hydrological situation. A regression model can never be perfect. In reality, spot price can be largely explained by the system load, while temperature has been used here as a proxy variable. Furthermore, evidently some explanatory variables are missing from the spot price equation. The load regression is not perfect, either, which can partly be attributed to the shortness of the data period.

The model's econometric reliability was briefly discussed in the previous section. Two problems were detected from an econometric perspective: autocorrelation and heteroscedasticity. In the spot price series, heteroscedasticity could be uncovered directly from the scatter plot (figure 14). This can be confirmed with the so-called Goldfeld-Quandt test for heteroscedasticity (Goldfeld & Quandt 1965). The null hypothesis of homoscedasticity can in this case be rejected at 0,1 per cent level.

A few correction methods for heteroscedasticity are suggested in Pindyck & Rubinfeld (1998, 148-152). Two of the methods require that either the residual variances are known or they are directly linked to an independent variable. While the latter assumption holds to some extent in the present case, the relationship between temperature and residual variance is not simple enough to facilitate the transformation suggested by Pindyck and Rubinfeld. The third correction method, heteroscedasticity-consistent estimation, produces consistent estimates of variances, but does not improve efficiency. Since heteroscedasticity does not cause biasedness in the estimates and the statistics are quite powerful, correction attempts are regarded unnecessary.

The second problem, autocorrelation, is present in both the load and spot price residuals. Serial correlation normally implies missing explanatory variables, which is evident in the case of the spot price model. Yet, the load model remains a question mark. The problem could probably be alleviated by running the regression separately for each month, since the effect of temperature is not constant throughout the year. The relative shortness of the data period does not permit this, though.

Generalised differencing and the Cochrane-Orcutt procedure have been suggested for the removal of serial correlation (Pindyck & Rubinfeld 1998, 160-164; Cochrane & Orcutt

1949). These methods were applied to the load and spot price models to reduce autocorrelation in the residuals. However, initial results did not show significant improvement to the original specification and so further elaboration was dropped. The model estimates remain unbiased, although less efficient than they would be in the absence of serial correlation.

This study is not primarily an econometric one. So, more advanced methods for model correction were not considered in order to leave space and resources for the primary objectives of this study. I consider the obtained results robust enough to justify proceeding with the research. Improvements are left for future research.

4.2.5 Normalised Load and Price Curves

Having determined the functions for load and price, it is possible to define the expected values for each day of a year. Actually, the true expected value will not necessarily be obtained, but rather a "normal" value for each day. The *normal value* is calculated by evaluating the functions at a normal temperature for each day. The normal temperature, in turn, is defined as the mean of temperatures for a given date over a 25 year horizon. In addition, the reservoir surplus is fixed to its long-term average, since its effect is attempted to be excluded from the analysis.

The normal load curve has other uses besides this analysis, as well. Namely, it can be used as a basis for hedging decisions. From the normal curve we get the monthly load profile, whereas the total energy volume can be estimated from other sources. Volumetric hedges must then be used to take cover from potential deviations from normal conditions, which is the topic of chapter five. Figure 23 shows the normal load curve.

The curve exhibits a rather strong trend downwards. The factors behind the trend are company-specific, such as changes in the customer base, and are unlikely to repeat themselves in the same manner. Notice that temperature has been normalised to draw the figure. Given that one is not concerned about the absolute level of load, but rather its expected day-to-day changes, the curve can be quite safely de-trended before utilisation. In other words, excluding non-repetitive exogenous factors, the expected load for a given day should be same for each year.

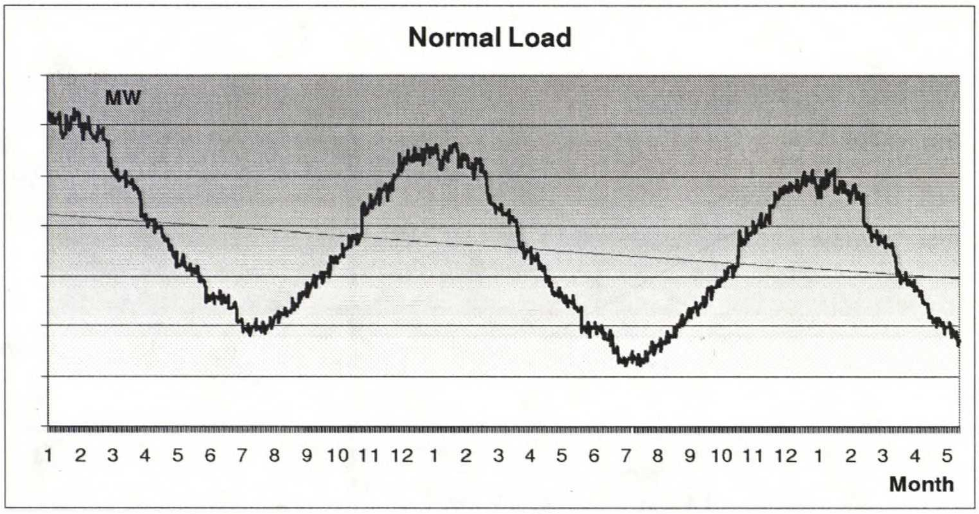


Figure 23: Normal load curve.

At this point it might be relevant to test whether the normal values derived above correspond to the expected values of the variables. This is done as follows. $\Delta P = P - E[P]$ and $\Delta V = V - E[V]$ are calculated for each data point by setting V and P equal to their empirical values and by substituting the normal values for their expectations. Observe that we need to extract the effect of reservoir levels from the empirical observations of P, since the expectations were calculated assuming a normal reservoir year. Of course, the reservoir level could have been fixed at any other level, as well.

Now, given true expected values, the means of ΔP and ΔV will tend to zero. Consequently, it is possible to perform a test on their empirical means with the null hypothesis of zero mean. The details of the test can be found in e.g. Dudewicz & Mishra (1988, 478-487). The test statistic $\frac{\bar{X} - \mu_0}{s/\sqrt{n}}$, where μ_0 is the null hypothesis and $s/\sqrt{n}$ is the standard error of mean, follows the Student's t-distribution. The null hypothesis is rejected at a given confidence level if the test statistic is larger than the critical value, which is obtained from the inverse of the distribution function.

The critical value is 2,58 for a 99 per cent confidence level. The mean of ΔV is 2,4 and the standard error of mean 1,62, yielding a t-statistic of 1,48. Since 1,48 << 2,58, the null hypothesis of $E[\Delta V] = 0$ cannot be rejected at any reasonable level. In other words, the model seems to give reliable results with regard to load. The mean of ΔP, in turn, is 0,45 and the standard error of mean 0,14, which gives 3,10 for the value of the t-statistic. The null hypothesis of $E[\Delta P] = 0$ is therefore rejected. Obvious reasons for the rejection would be model misspecification and the potential bias proved by the Jensen's inequality (see section 4.2.1). In particular, the regression model is not capable of explaining extreme spikes.

4.2.6 Historical Analysis of the Exposure to Temperature

In these two last sections of chapter four the model will be put together and the effect of temperature will be evaluated in financial terms. The historical realisation of the joint effect of price and load deviations will be first looked at and, subsequently, the marginal effect of temperature is estimated by simulation. Historical analysis paints a picture of the problem, but is inadequate for providing the distributions, on which hedging decisions will be based.

The inclusion of the extreme winter of 2003 has both positive and negative implications for the study. First, since the data period for load is less than three years, most statistical measures will be exaggerated by the overrepresentation of extremes. On the other hand, since those extremes have motivated this study, it is rather essential to get a feeling of their graveness.

The historical analysis is performed as follows. First, ΔP and ΔV are calculated for each day, as was explained in the previous section. Then their joint distribution, as well as the distribution of their products, can be assessed. Lastly, some statistics may be calculated based on the distributions.

Figures 24 and 25 present the joint distribution of load and price deviations. What is immediately evident from the figures is the skew of the distribution, which is in agreement with expectations. As a matter of fact, the expected value can be located in the upper right area of plot in figure 24, whereas the median tends to the origin, both in theory and practice. In other words, most of the sample points can be found below the average, but the extreme occurrences, which seem to happen only on the positive side, lift the average significantly above zero. The linear correlation coefficient between ΔP and ΔV is as high as 0,44. Yet, as their relationship is not linear, this linear measure may not be relevant. As a matter of fact, the correlation for observations left to the origin is only 0,07, while the correlation for observations on the right side of the origin is 0,57.

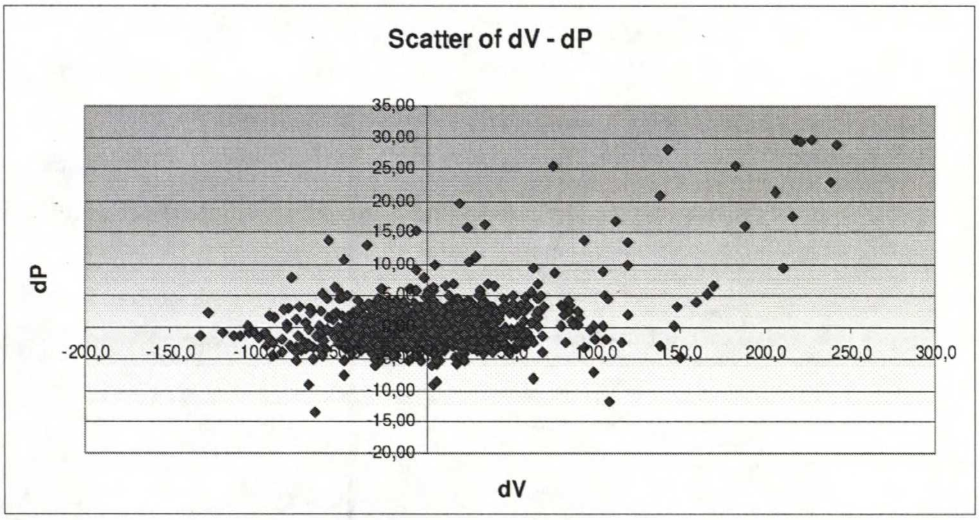


Figure 24: Scatter plot of dV and dP.

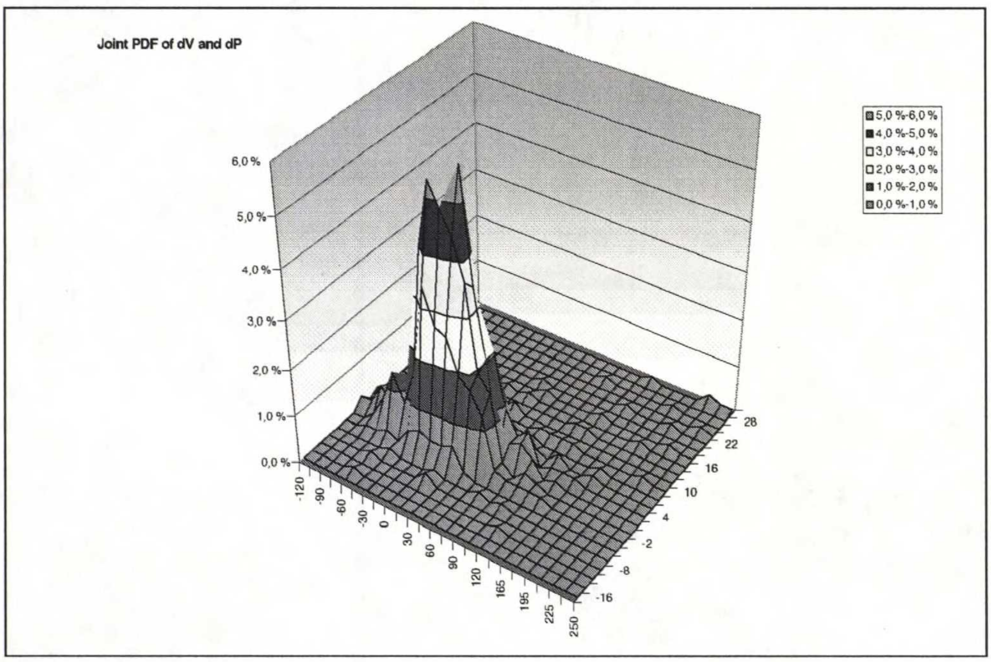


Figure 25: Joint pdf of dV and dP.

It may also be useful to examine the probability distribution of the product of ΔP and ΔV, since that was identified as a major source of uncertainty in cash flows. Figure 26 exhibits both the probability density function and cumulative distribution function of $\Delta P^*\Delta V$. However, because of the delicate nature of the actual financial implications for Vattenfall, the euro amounts on the horizontal axis have been scaled so that their average corresponds to 100. Also, proportionally equal length has been cut off from both tails in order to fit the picture on the page. Despite the relative scarcity of data points, the long tail to the right can be distinguished. Most of the observations are centred around zero, as they should. The median corresponds to roughly 6 per cent of the average.

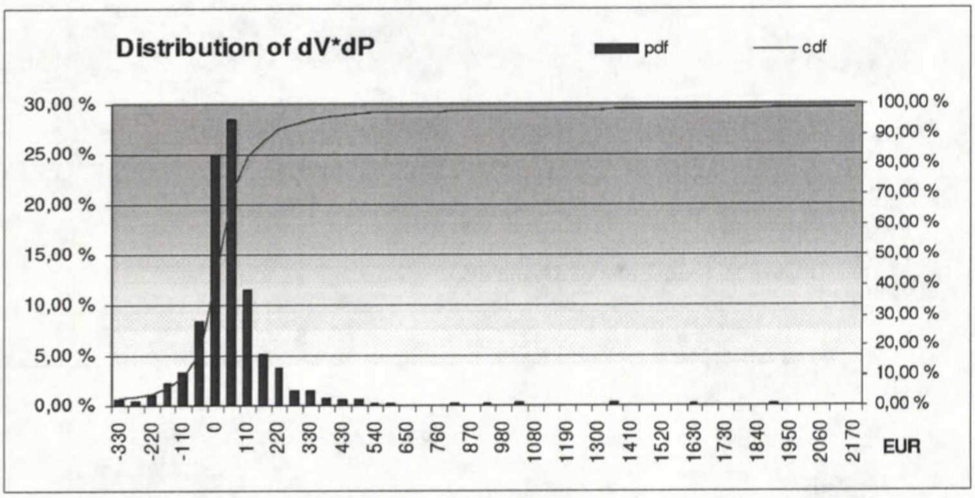


Figure 26: Probability distribution of dV*dP

Finally, the "loss function", i.e. the extra costs ($\Delta P^*\Delta V$) incurred as a function of volume deviation or, eventually, temperature deviation from the norm, will be discovered. To reveal the historical loss curve, the term $\Delta P^*\Delta V$ has been sorted by load deviation. Figure 27 shows the loss curve derived in this manner. The numbers are scaled with the same factor than in the previous figure to retain comparability. Hereafter, all euro amounts will be scaled with the same factor.

The curve implies quite stable conditions until load is increased sufficiently as a result of colder weather. After a certain point the curve steepens very sharply to reach a level of almost 80 times the average. The figure therefore confirms that the main concern is to get coverage from extreme events rather than small deviations from the norm.

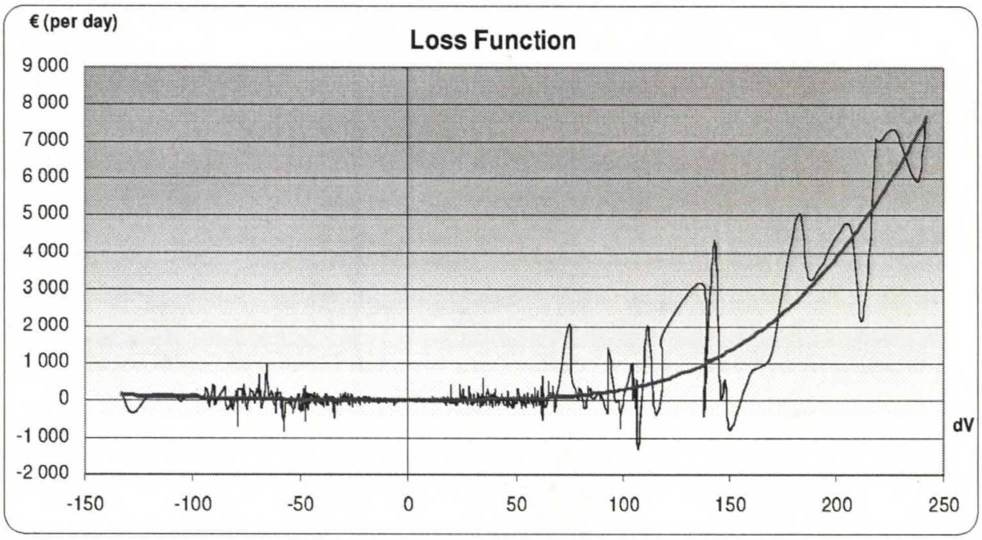


Figure 27: Historical loss curve.

4.2.7 Simulation of the Loss Curve

Figure 27 above is still not sufficient for reliably assessing the marginal influence of temperature on cash flows. On the contrary, far more observations of the extremes to are needed to determine the exposure to be hedged. Since empirical data is scarce, we need to perform simulations based on the sample. First, the simulation methodology is briefly presented and, subsequently, the results.

First of all, the time of the year, which was not considered in the historical analysis, has a major effect on the severity of the repercussions of temperature deviations. For instance, a –15 degrees' difference in late March results in conditions of roughly –15° Celsius, whereas a similar deviation in January takes the temperatures far below –20 centigrades. The difference in the financial impact can actually be many-fold, which is primarily due to the non-linear shape of the loss curve. As a consequence, I have chosen to perform the simulation separately for each calendar month. In fact, only the month of January will be examined in the rest of this study, but the methodology is easily extended to other months, as well.

The simulation model is a hybrid in the sense that each value is generated as the combination of fundamental-based functions defined above and one or more stochastic components. Furthermore, the stochastic part is calibrated to agree with the results on regression residuals in sections 4.2.2 and 4.2.3.

The actual simulation is performed as follows. For each day of the chosen month, temperature is fixed at the sum of the norm for that day and a given deviation from the norm, which is maintained constant throughout the month. Load and prices are then jointly simulated for the whole month and deviations from the normal values are calculated (definition of normal values was given in section 4.2.5). The procedure is repeated so that thousands of realisations of the chosen month are generated for *each* desired level of temperature deviation. I have restricted the deviations to range from +15 to –20, so that the coldest temperature to occur in the simulation is –29 centigrades.

The simulation model is mathematically described by the following discretised equations.

$$\Delta x_t = \Delta L_t(.) + \sigma_L \sqrt{\Delta t}\,(m_t - m_{t-1}) \tag{4.5}$$

$$m_t = \rho^{t-1}\varepsilon_1 + \sum_{j=2}^{t} \rho^{t-j}\varepsilon_j (1-\rho); m_0 = 0 \tag{4.6}$$

$$\Delta y_t = \Delta p_t(.) + \sigma_p \sqrt{\Delta t}\,(\eta(y_{t-1} - p_{t-1}) + (1-\eta)\varepsilon_t) + p_t u_{1t} \kappa (u_{2t} < \phi \Delta t)(T_t < -15°C) \tag{4.7}$$

where Δx is the change in load during Δt and Δy is the change in the logarithm of price. The deterministic change in load and the logarithm of price are marked as $\Delta L(.)$ and $\Delta p(.)$, respectively, when all the parameter values for the functions $L(.)$ and $p(.) = \log(P)$ (see sections 4.2.2 and 4.2.3) are given. The terms σ_L and σ_p are the annualised volatilities of load and price, which can be estimated as the corresponding (annualised) standard errors of residuals. The time step Δt is then one day or 1/365 of a year. ρ and η are the respective autoregression coefficients of load and price residuals, which are estimated with a simple OLS regression. ε is an independent standard normal random variable, whereas u_1 and u_2 are independent uniform (0,1) random numbers. Finally, κ is the maximum jump size and ϕ is the average number of jumps per year under colder than

-15° conditions (T<-15). The term $(u_{2t} < \phi\Delta t)$ is taken to be one if the condition is true and zero otherwise – this generates jumps randomly at the correct average frequency in the limit as Δt tends to zero (Clewlow et al. 2001). Similarly, $(T < -15)$ is taken to be one if the condition is true and zero otherwise.

The model probably needs some further clarification. Equation 4.5 explains the load process, which is rather simple. Clewlow et al. (2004) discuss the simulation of load with a hybrid model, such as used here. However, an autoregressive component has been added to both the load and price equations, which is justified by the regression results. The autocorrelation coefficient is estimated with the following regression equation.

$$e_t = \alpha + \rho e_{t-1} + \varepsilon \tag{4.8}$$

e_t = residual t

α = constant; ε = error term

ρ = model coefficient

The stochastic part of the equations 4.5 and 4.7 are then a weighted average of previous stochastic parts and a fresh random element. This way the model can account for the fact that deviations from the model are caused by some omitted real factor.

In addition, the spot model is modified so that it is capable of producing some of the jumps seen in the time series. These jumps are most likely produced by sudden changes in supply condition, which often last for some days. The lingering of the effects is captured by the autoregressive nature of the process. However, not all jumps necessarily relate to cold weather, as such. Therefore, the jumps have been restricted to occur only during conditions of -15°C and colder.

Clewlow et al. (2001) and Du (2002) discuss mean-reverting jump diffusion processes. They model the jump size as lognormally distributed around its mean. Nonetheless, that approach does not give acceptable results here. Particularly, normally or lognormally distributed jump size gives far too large jumps from time to time. What seems to work better in this case is a uniformly distributed jump size between zero and the maximum proportional jump size estimated from historical data. Jump frequency is also estimated from historical data. The historical data used here has been deprived of the effect of hydrology and is restricted to observations with temperature below –15°C.

One more thing should be commented about the above model. Namely, since price movements are quite likely to take the same direction with changes in load, the standard normal parameter ε_t is the same in both equations.

Figure 28 below shows the result simulation for the month of January. Temperature deviation from the long-term average can be read from the horizontal axis, while the associated average loss is exhibited by the blue curve. The dashed curves present the upper and lower bounds for a 95 per cent confidence level. These results, coupled with the corresponding probability distribution of temperatures, can now be utilised for hedging purposes.

Compared with the historical loss curve of the previous section (figure 27), the simulated average curve is very similar until a temperature deviation of around -12°C. However, up from that point it is the upper bound curve that follows better the historical curve. The extreme end in the history was produced by January and February 2003. The prices were then kept up by a number of factors along temperature. In that respect, it seems realistic that those observations are closer to the upper bound than the average.

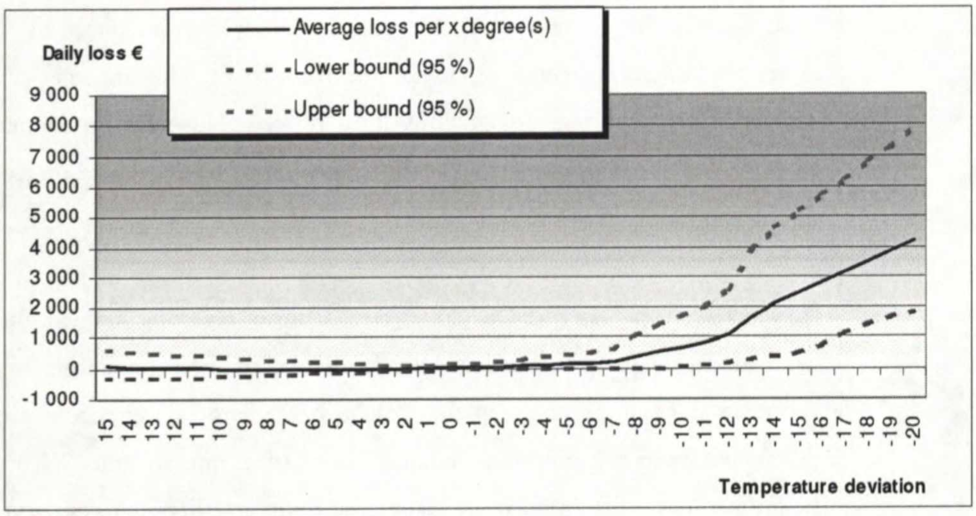


Figure 28: Simulated daily loss curve for January (scaled).

In spite of the fact that it would be desirable to hedge each day separately, the standard weather products on the market currently have a minimum time span of one month. To assess the exposure to fluctuations in the monthly average temperature, some additional simulations are needed. Consider a month with five days of –20°C below the norm and rest of the days very close to normal temperature. According to figure 28, the daily loss in the cold days would rise up to 4000 on average, giving a monthly loss of 20 000, which corresponds to 200 times the expected daily loss. On the other hand, a month with all days only -3°C below the norm would result in the same monthly average temperature, whereas the losses in this case would be almost negligible.

The above example proves the necessity of assessing the monthly exposure separately. The simulation is done in the following manner. All instances of the chosen month (here January) are picked from the historical temperature data. Next, the simulation model presented above is applied to each of the months one by one to get the cumulative loss figures. The simulation is repeated several thousands of times for each month selected from the data. As a result, we get the distribution of losses corresponding to the monthly average temperatures.

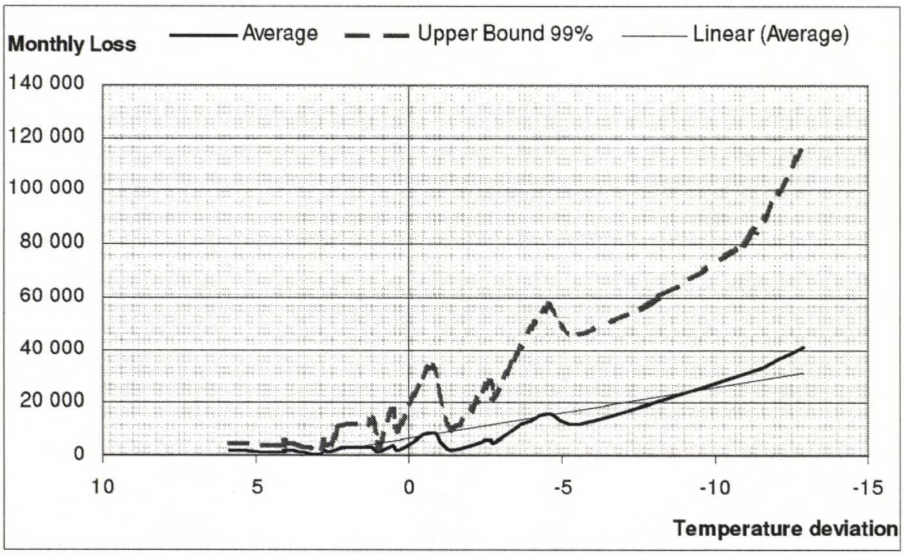


Figure 29: Monthly loss curve for January (scaled).

Figure 29 gives the simulated monthly loss curve for January. The average curve is amazingly linear compared with the daily loss curve in figure 28. However, the upper bound curve shoots off, once again implying that it might be reasonable to seek cover from the extreme conditions separately and use another hedge to smoothen the average cash flow. The bumps in the figure relate to the variance of temperatures, which was given as the justification for the monthly analysis. For a comparison, the average temperature of January 2003 was -5°C below the norm and the losses incurred were close to 60 000.

Chapter five will next look at different hedging alternatives and a performance analysis of weather contracts will be carried out.

5 APPROACHES TO WEATHER RISK MANAGEMENT

According to Ramamurtie (1999) there are two ways as to managing weather risk exposures. The first concentrates on insuring against catastrophic events, which are also characterised as low-probability high-impact events. The other type of risk mitigation is aimed at reducing the variance of cash flows deriving from changeable weather. In this study the emphasis is on the latter.

To begin with, difficulties in the implementation of hedging strategies are at least as plenty as available solutions. Although standard products, such as exchange-traded temperature swaps, offer better liquidity and more competitive pricing, they rarely fully match the hedgers' needs. The underlying index in standard products is usually based on a cumulative temperature measure over a certain period, often three or six months. Nonetheless, the losses are frequently incurred on individual days or hours when both load and price temporarily take off. As a result, as temporary temperature peaks easily get averaged out in the accumulative index, such products do not necessarily provide a sufficient hedge against extreme spikes. A weather hedge would only be effective if the contract was for a short period of time - a week, for instance. (Locke 1998)

Also basis risk is present, since the underlying temperature index in the contract may not correspond to the actual temperature development within the area determining the demand to be hedged. (op. cit.)

5.1 The Ideal Hedge

The definition of volumetric risk in chapter 4 permits the notion of a perfect hedge. Given that the entire problem is created by the last term in equation 4.1, $\Delta V * \Delta P$, a perfect hedge would be one that pays the positive price difference for each MWh above the expected volume and the negative price difference for each MWh below the expected volume, respectively. In other words, the hedge could be formulated as $\max(\Delta V, 0) * \max(\Delta P, 0) + \min(\Delta V, 0) * \min(\Delta P, 0)$. What is more, if the hedge was priced at the discounted expected payoff, i.e. no risk premium was demanded, no profits would have to be given up on average in exchange for the perfect elimination of weather-induced fluctuations in cash flows.

As a matter of fact, a product known as swing option, or equivalently take-or-pay option, allowing for a degree of such flexibility in energy procurement is commonplace in the natural gas industry (Barbieri & Garman 1996). Take-or-pay options are also described in Kaminski et al. (2004, 136-145). The structure of a swing contract is such that minimum and maximum daily volumes that can be bought at a fixed price are determined. The volume is allowed to swing between those boundaries as long as the cumulative volume for the contract period falls between certain limits. Normally, if these cumulative limits are violated, the buyer has to pay a penalty. The problem with application to volumetric risk is that the retailer, i.e. the buyer of the hedge, can always exercise optimally against the spot price, which implies an over-hedge, since prices are likely to rise from time to time irrespective of the retailer's sales volumes.

A case study by GuaranteedWeather (s.a.) presents an innovative weather derivative structure that protects the subject from both volume and related price risk without over-hedging the exposure to price risk. The contract hedges the precipitation risk of a load-serving utility by paying a predetermined amount in years of low precipitation. The number of payments increases as precipitation declines, hedging the utility's volumetric risk. Moreover, the amount of each payment increases as electricity prices rise, eliminating the related price risk. There is no up-front payment attached, but the utility will compensate for the risk reduction by paying the writer of the hedge in years of high precipitation. Such a structure could be ideal for hedging temperature risk, as well.

On the other hand, one might consider hedging with more or less standardised option contracts. The problem with daily power calls is similar to that of swing options explained earlier. Price peaks are not always related to temperature and therefore these option can be unnecessarily expensive (Ellithorpe & Putnam 2000). According to Ernst (2003), *weather-contingent options* would offer a more satisfactory alternative, as they are triggered by the weather and could be purchased for much less than the cost of standard options. His experience from the natural gas markets indicates that a weather trigger can reduce option premiums by as much as 50 to 75 per cent. Ramamurtie (1999) remarks that temperature contingent daily power calls can be offered at a lower cost, since the probability of both strikes being hit at the same time is relatively low.

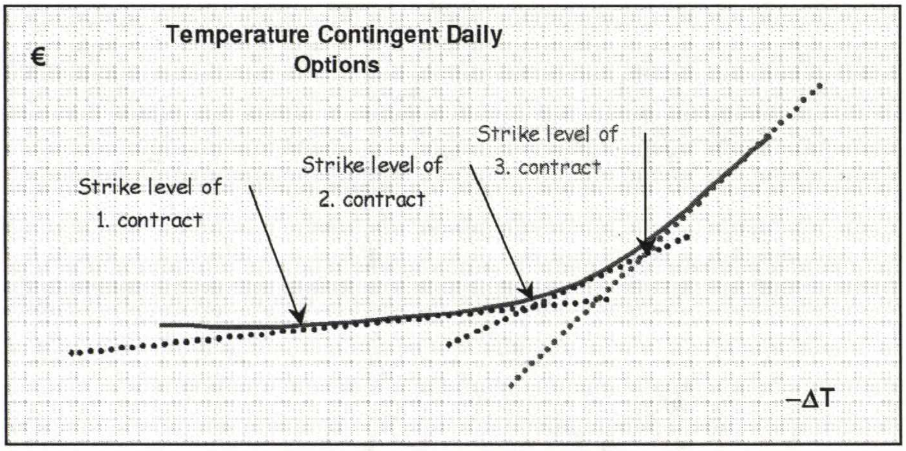


Figure 30: Temperature Contingent Daily Options

Figure 30 considers a strategy using temperature contingent daily power calls. At each point on the horizontal axis a volume difference corresponding to the temperature can be estimated. The estimated volume difference can then be used to determine the number of calls to be purchased. It is thus possible to imitate the loss curve by increasing the number of calls, as outdoor temperature gets colder. A strategy of three calls (of potentially different volumes) with the same strike price, but different temperature triggers is depicted in figure 30. Actually, providing volume and temperature move hand-in-hand and in accordance with the assumed model, this strategy gives an almost perfect hedge against temperature-induced volumetric risk, since the payoff is sensitive to both realised price and temperature.

5.2 Other Solutions

The weather market, which was touched in chapter 3, has yet to prove its full exploitability, as it is still plagued by relative illiquidity (Dischel 2002). As a consequence, potential hedgers might want to consider other alternatives, as well. Two alternative solutions are discussed in this section. The first is hedging the risk with derivatives on the commodity itself and the other deals with internal solutions within the group.

5.2.1 Over-Hedging of Expected Volume

The idea of hedging volumetric risk with power derivatives is based on the non-linear relationship between prices and load. Peaks in load normally entail increasing prices and vice versa. A long position in a power derivative can therefore have a smoothening effect on cash flows, since it pays out when volumes are larger than expected, i.e. when the losses are greatest, and increases losses when they would otherwise be smaller. The use of power derivatives is here called over-hedging, for it means hedging more than the expected volume.

This strategy actually has severe drawbacks that need to be discussed. Consider first that only temperature besides normal randomness affects spot prices. In that case, a simple forward hedge can be thought to perform quite satisfactorily. The variance of cash flows can be reduced, as both extremely large and smaller losses are exchanged for moderate losses. However, the first dilemma is that a substantial forward position is required to offset the extremely big losses. In consequence, there is a huge downside potential, too.

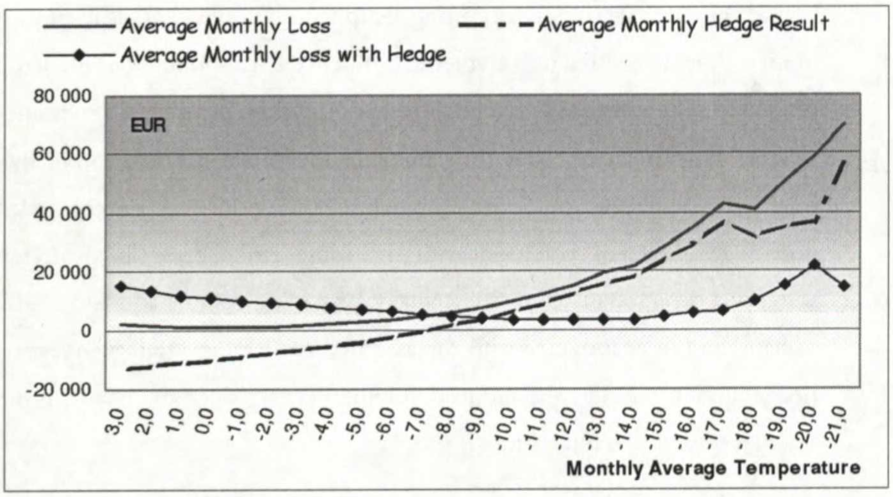


Figure 31: Monthly forward hedge (34 % of expected volume).

Figure 31 exhibits the effect of a monthly forward hedge. The figure was produced by applying the temperature simulation method described in section 5.3 and the simulation model of section 4.2.7. The red line (the upper increasing line) shows the unhedged average loss for a given monthly average temperature in January. The dashed line, in turn, is the average hedge result, where the realised monthly average price is settled against the expected spot price, i.e. the average over all simulations. The size of the hedge was set at 34 per cent of the expected load, which corresponds to the largest conceivable increase in average load. The blue line with dots, in turn, is the hedged loss curve. Notice that the hedged and unhedged curves intersect very close to the expected temperature for the month, which is –6,8°C. In addition, the probability of the average temperature resulting above the expectation is around 59 per cent. In other words, the hedge has eliminated the extremely big losses and produced a higher frequency for losses somewhat above the expected loss. As a matter of fact, the variance of the cash flows has been reduced by over 50 per cent.

However, the picture above does not tell the whole truth. Namely, it is based on average figures over tens of thousands of simulations. The substantial downside risk might thus be a matter of concern to risk managers. Option contracts could be thought as an alternative, since they provide the same protection without the downside risk. Yet, at-the-money options for a large volume can in reality prove to be a quite expensive solution. Another thing is that the loss curve steepens faster than the payout curve of an at-the-money option. Hence, out-of-the-money options could possibly be considered in order to reduce the cost and to mimic the shape of the loss curve.

Nonetheless, the option strategy is not as straightforward as it first seems. First of all, standard options traded on Nord Pool and OTC-markets have electricity forwards as the underlying products (see section 2.3.5). In other words, the financial settlement is not made against the spot price, even as spot price was identified as the other component of volumetric risk. So, the options would have to be Asian options on the monthly average price if they were to be used in hedging volumetric risk. Second, out-of-the-money power options have a strike price higher than the expected spot price, which reflects the fact that they are price hedges, not volumetric hedges. This problem will be illustrated by an example.

Consider just for a moment that Asian options on power can be purchased for any strike level and that the temperature loss curve is stepwise linearly increasing, as in figure 32. It is also implicitly assumed that the volume deviation is constant during each linear piece of the curve. Out-of-the-money option are next employed to reproduce the loss curve. For instance, at point A of figure 32 the spot price corresponding to the temperature can be estimated. This price estimate is chosen as the strike price of the first option, the volume of which is set equal to δ. Likewise, the strike price of the second option is set equal to the estimated spot price at point B and the volume is fixed at $\gamma - \delta$.

The problem with the strategy is following. The losses at some point of the steeper part of the curve would amount to $\gamma^*(P - X)$, where P is the realised price and X denotes the expected price. Yet, the options would only pay the amount $(\gamma - \delta)^*(P - P_B) + \delta^*(P - P_A)$, where P_B and P_A are the strike prices of the first and second option, respectively. Their difference yields $\gamma^*(P_B - X) + \delta^*(P_B - P_A)$, which is the part of the loss not covered by the hedge. Given that in reality the volume deviation is not constant, it is quite impossible to devise a proper strategy using out-of-the-money options.

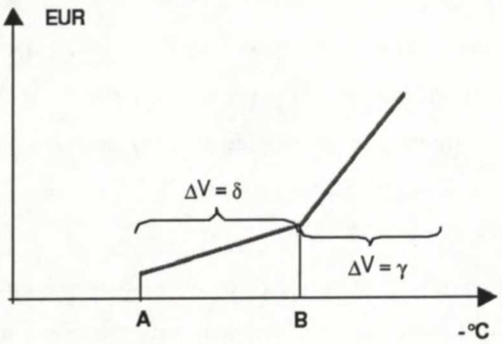


Figure 32: Stepwise linear loss curve (illustration).

Now that some other problems have been demonstrated, the earlier assumptions can be given up. First, Asian options have not been adopted as standard products by the market. The purchase of such options would thus require bilateral negotiations. However, this would probably not be very wise, since the efforts could as well be directed to structuring a proper weather hedge. Second, prices are not driven solely by temperature. As a matter of fact, according to the data used in this study, temperature alone explains less than 40 per cent of the variance of prices. Put another way, there is over 60 per cent of pure speculation in every price position assumed with the purpose of hedging temperature-induced volumetric risk. After realising this, the 34 per cent of the expected customer load used to produce figure 31 is quite a substantial position. On the other hand, there is little point in taking very small positions, since that would leave a major part of the exposure unhedged and would therefore have a negligent role in stabilising retailer profits.

5.2.2 Internal Reconciliation of the Risk

Internal hedging might be appropriate if the business unit in question is a part of a larger group that has a stake in every part of the value chain. For example, producers probably make more profit in moderately cold winters when consumption and prices are high than in warm winters. Hence, their risk is at least partially opposite to that of retailers. It might therefore be beneficial to both the retailers and producers to cover each other's losses to some extent. Moreover, as the business units would belong to the same group it would be easier for them to agree on terms and valuation of the hedges, which implies that they could trade on very thin spreads.

Ideally, there would be an internal market place for weather risks where the exposures could be matched and traded internally. In addition, the aggregation of weather risks across the group would reveal the overall weather exposure of the group, which could then be traded away on an external market. Naturally, a sufficiently liquid and functioning external market would be a prerequisite to this scheme. In fact, as regards the Nordics, the Chicago Mercantile Exchange offers monthly and seasonal weather futures for Stockholm (Chicago Mercantile Exchange 2004). Also Vattenfall has begun to offer weather derivatives to its customers on the Nordic market (Vattenfall AB 2003b, 9).

The establishment of an internal insurance unit could be another alternative. This unit could then sell structured weather insurances to other business units. Thus, the insurer would benefit from diversification across different functions, as well as geographical areas, and could use actuarial methods to determine the required risk premia. Given that the insurance unit would be a non-profit cost function, all possible profits could be refunded to the business units from time to time, thus ensuring that no profits would need to be given up in exchange for the insurance. Of course, possible losses would also need to be passed through to the respective business units.

The approaches in this section are only ideas and their pros and cons have not been developed any further. Internal hedging definitely should be thought of within large groups. Nonetheless, such an approach requires a group-wide project to be set up and takes time to be implemented. It is not in the scope of this study to go into details of such project.

5.3 Simulation of Temperatures

Section 3.2 dealt with pricing and it became clear that a simulated distribution of temperatures is necessary for the valuation of temperature derivatives. In addition, a simulated distribution is needed for risk management purposes to evaluate alternative hedging strategies. The simulation model used in this study is described next.

To begin with, it is necessary to use daily values of history, rather than seasonal values, to uncover the meteorological sequence and to have enough data points. The model should incorporate some sort of mean-reversion to reflect the fact that temperatures cannot rise or decrease day after day for a long time. It should also include randomness of day-to-day temperature changes. In the suggested model the future distribution is bootstrapped from the actual history of temperatures. (Dischel 1999b)

The model proposed by Dischel (1999b) can be presented in finite difference form as follows.

$$\hat{T}_{n+1} = \alpha\Theta_{n+1} + \beta\hat{T}_n + \delta\Delta T_{n,n+1} \tag{4.9}$$

$\hat{T}$ = simulated temperature

α, β, δ = constant parameters to be estimated

Θ = time-varying daily temperature averaged over many years for each date

$\Delta T_{n,n+1}$ = randomly chosen daily temperature change

The parameters in the model are restricted so that $\alpha + \beta = 1$ and $\delta \leq 1$. A balance must be found between the strength of mean reversion, or α, and the influence of δ. The parameters are then calibrated to the historical distribution so that desired properties, such as average, standard deviation and skew, match between the simulations and the history. An optimisation procedure could be developed for this purpose, but a simple trial and error approach is used here to find the values for the two parameters.

It is noteworthy that the model does not make any assumptions about the shape of the distribution, but the bootstrapping reproduces the properties of the historical distribution (Dischel 1999b). To simulate temperatures e.g. for January the simulation is begun at a date well in advance, say the first of December. The seed can be set equal to the starting date's average temperature (Θ). The expected temperature (Θ) for a given date is calculated as the average over the span of the data (25 years) for that particular date. There are 25 instances of December 1st, for instance, in the used data.

For the next day's temperature the next day's Θ and a selection from ΔT is needed. Consider ΔT is the change in temperature between December 2nd and December 1st. The array of possible values of ΔT then consists of the 25 temperature changes between those dates found in the historical data. To project the temperature for December 2nd, ΔT is randomly picked from the "sample space", weighted by delta and added to the weighted average of December 1st temperature and Θ for December 2nd. The sequence is repeated until the desired period is completed. (Dischel 1999a)

The use of Dischel's model is justified, since it gives fairly reliable results and reproduces the historical shape of the temperature distribution. Also, McIntyre & Doherty (1999) successfully implemented the model in the U.K. with the difference that they used normally distributed daily temperature changes instead of utilising the historical sample. The model developed by Alaton et al. (2002) is slightly more complex but gives support for such modelled properties as mean-reversion.

Figure 33 shows the outcome of 35 000 simulations for January where the beginning date for the sequence was first of December. The average of mean temperature for January is around -6,5°C and standard deviation is 6,8°C. A discerning eye will also notice that the distribution is slightly skew to the left, i.e. extremely cold Januaries are more likely than extremely hot ones. It must be added here that a cut-off temperature at +7°C was used in the simulation, since that is the warmest temperature observed during December and January in the existing history.

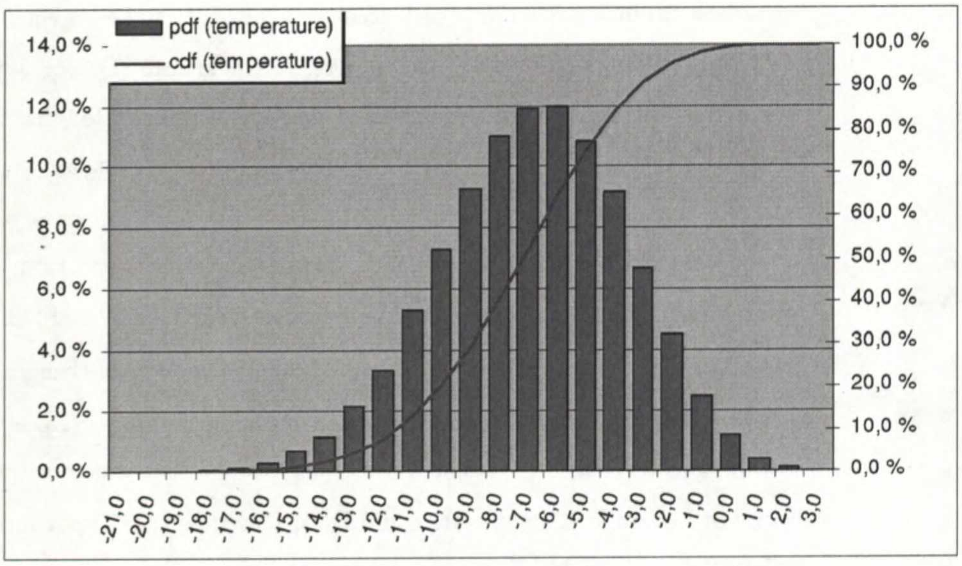


Figure 33: Distribution of average temperatures (January).

5.4 Assessment of the Alternatives

5.4.1 Feasibility of the Alternatives

Chapter three presented some characteristics of the weather market and introduced four type of weather hedges: swaps and options, weather-linked bonds, insurances, as well as structured deals. Furthermore, section 5.1 discussed the composition of an ideal hedge and in section 5.2 two alternative approaches were considered. Before moving on to testing the performance of the hedges and making recommendations, it is warranted to assess the feasibility of the alternative approaches to the retailer that forms the starting point of this study.

To begin with, insurance contracts are designed to give coverage from low-probability high-impact events, such as rough storms. The requirement of demonstration of loss and evidence of the link between this loss is something that holds back the usability of insurances in dampening the variability of profits. Another disadvantage of insurances is that they only compensate for the damage that can be substantiated and does not as such respond to the intensity of the weather event. Therefore, insurances cannot be regarded a viable alternative for hedging volumetric risk.

Weather-linked bonds, for their part, would be a more sensible choice. For instance, a structure similar to the 'volatile winter' of section 3.1.2 would be suitable for smoothening temperature-dependent revenues. Yet, the issue with weather-linked bonds is that they require that capital be either invested or borrowed and that they do no regularly trade on the market. While this type of contract deserves consideration, it is perhaps not relevant in the very short-term.

Standard power derivatives were proposed on grounds of the non-linear relationship between prices and load. However, section 5.2.1 provided several arguments against the use of price hedges in hedging volumetric exposure. First, weaknesses of an option strategy were shown. The fact that Asian type option are not a standard excludes power options from the list of practical solutions. Secondly, forward contracts were deemed unwise, as the assumed position would be more speculative than protective.

In addition, internal reconciliation of the risk was given a thought. This is something that definitely should be merited more attention within large groups that have a stake in each part of the value chain. Different business units have exposures that could be partially cancelled out and the residual could be dealt with on an aggregated basis. However the study of the benefits and disadvantages of such an approach are left for future research.

Eventually, the advantage of temperature swaps and options is that they are directly linked to the main determinant of customer load and their payout is proportional to the intensity of the weather conditions. Also, this kind of weather derivatives begin to be quite well understood and, despite a few setbacks, they are gradually gaining popularity around the world. Alaton et al. (2002) remark that different actors on the market can have opposite exposures and that weather derivatives make it possible for them to hedge each other's risks. The performance of these contracts will be evaluated in the next section.

Lastly, daily temperature-contingent power options were identified as rather ideal contracts for hedging volumetric risk. The decisive property of these contracts is that their payouts are sensitive to both temperature and price. It was argued in section 5.1 that a combination of many such options with different strike levels gives an almost perfect hedge, not only against temperature variations, but also against other factors that contribute to the size of volumetric losses. The next section will assess how a temperature-contingent power option perfoms on a monthly basis, i.e. when the contract has a monthly settlement against the monthly average price.

5.4.2 Performance Analysis of Weather Contracts

This section will analyse the perfomance of two alternative strategies. The first is a combination of an HDD swap and out-of-the-money HDD options, while the other consists of temperature-contingent power calls and an HDD swap. For practical reasons, the analysis will be done on a monthly basis, i.e. the payouts are determined by monthly average values of temperature and prices. Month is usually the smallest interval for which contracts are sold. As before, the focus is on January alone.

The analysis is based on simulation using the models developed in sections 5.3 and 4.2.7. The procedure begins with a simulation of temperatures for each day of a January. Subsequently, the load and price equations are evaluated at these temperatures and the simulation equations 4.5-4.7 are used to obtain a load, price and volumetric loss figures for each day. Finally, the monthly averages of temperature, price, load and volumetric loss are calculated. Average temperatures are rounded to closest integer to make the analysis easier. The simulation is then repeated tens of thousands of times to get reliable estimates also in the tails of the distributions.

After completing the simulations, it is straightforward to assess the perfomance of various hedging strategies, as the payouts from monthly hedges only depend on the average temperature and/or average spot price. In addition, the fair price of the hedges is obtained as a by-product of the analysis. The fair price is simply the average of payouts over all simulation outcomes. However, in reality a risk premium is very likely to be added on top of the fair price.

Strategy of Temperature Swap and Options

The first strategy to be evaluated is a combination of an HDD swap and two out-of-the-money HDD call options. The options are included simply because the exposure was found to be non-linear, whereas the payout scheme of each of these derivatives is linear. By having three different strike levels, i.e. points where the payout curve is steepened, the shape of the loss curve can be imitated. The analysis is based on centigrades, which does not change the results in any way, since centigrades are linearly related to heating degree days (see the definition in section 3.1.1). The cut-off level at 18°C does not have an effect, since temperatures never get that high in January.

The appropriate tick size and strike values are determined by looking at the simulated unhedged loss curve (see figure 34). Accordingly, the strike values for the options are chosen at -10°C and -15°C, which correspond to values -3,2°C and -8,2°C in figure 34, as the expected temperature is -6,8°C. It is assumed that the swap is fairly priced at the expected value, although this might not be so in reality. The average increase in loss per one degree's decrease in temperature between 2,8°C and -3,2°C is about 1125, which is chosen as the tick size of the swap. The changes left to 2,8°C are neglected because the curve is practically flat beyond that point. Similarly, the average change in loss between -3,2°C and -8,2°C is slightly over 3700. However, 1125 of that is already covered by the swap, so only the difference needs to be hedged by the option. The tick size of the first option is thereby set equal to 2500. By similar reasoning, an adequate tick size for the second option is found at 2500.

Figure 34 gives an idea of how well the above hedging strategy performs. The loss curve has changed from a non-linearly increasing to almost flat curve. The hedged curve does include the fair cost of the options, but the cost may in reality be higher because of potential risk premia. The variance of the loss amount has been reduced to less than half of that of the unhedged loss. In contrast, the higher moments of the loss distribution have not changed significantly.

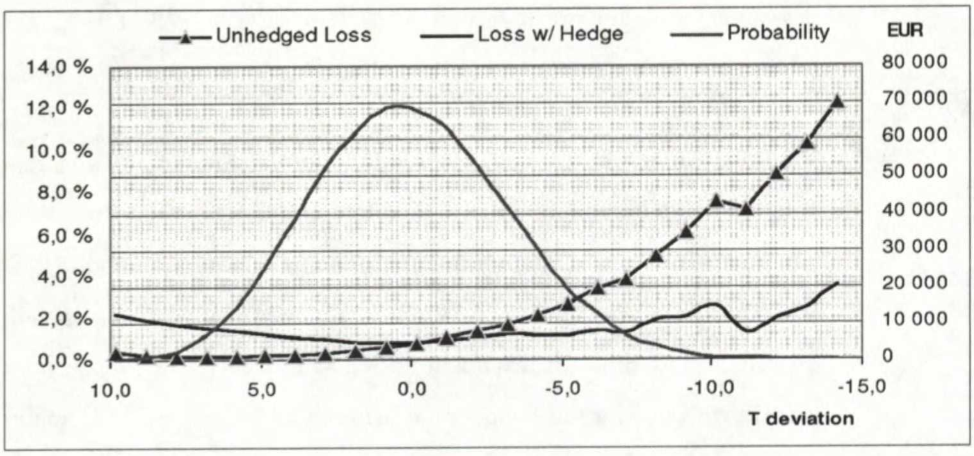


Figure 34: Hedging with HDD swap and calls.

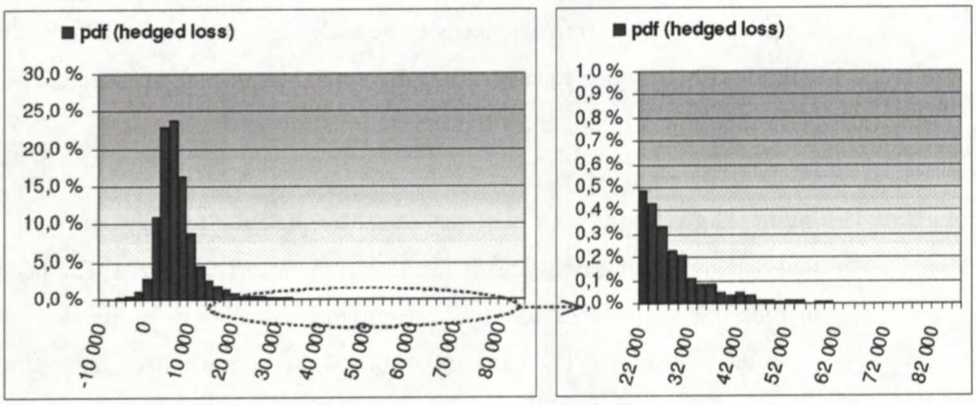


Figure 35: Distribution of hedged loss.

Let us examine more closely the probability distributions, particularly the tails. Figures 35 and 36 display the probability distributions of hedged and unhedged losses. Notice that the hedged distribution has moved slightly rightwards. This is the cost of nearly eliminating the extremely big losses. On the other hand, judged by the tails of the distributions, which are shown on the right-hand side, the hedging has been quite successful. A great part of the tail has been removed. As a matter of fact, the probability of incurring a loss greater than 12 000 has been reduced by 5,5 per cent.

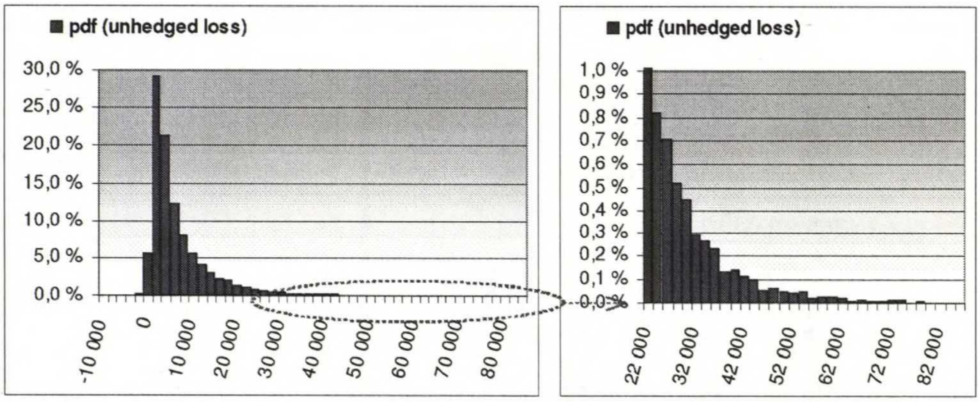


Figure 36: Distribution of unhedged loss.

Strategy of Monthly Temperature-Contingent Power Options

Instead of using daily temperature-contingent power calls, the second strategy under scrutiny comprises their monthly counterparts. The justification is that it is already quite certain that the daily option would perform very well and that monthly contracts might be easier to arrange. For instance, monthly contracts would need to be settled only once for each month. Moreover, the lower volatility of monthly prices make them easier to predict compared with daily prices, which makes the valuation easier. Lastly, monthly forward contracts are traded on Nord Pool for six nearest months, which can help the seller better manage its risk.

The strategy is composed as follows. The strike price of these dual trigger options is set equal to the expected monthly spot price. Options are then bought so that there is one for each negative deviation from the expected temperature (-1, -2, …, -14) and the temperature triggers of these are set equal to the average temperature corresponding each deviation. Next, the volume of each option is determined from the simulated monthly average load figures. For each option, the volume is set equal to the marginal increase in volume with respect to temperature. Mathematically, that is the absolute value of the derivate of load with respect to temperature multiplied by the number of hours in January.

An example will clarify the strategy. Suppose that the expected monthly price is 21 €/MWh and the expected average temperature is roughly -7°C. Then, the strike price of the first option, as well as of all the other options, is 21 €/MWh and the temperature trigger is -8°C. Next, if the unconditional expectation of load is assumed to be 100 MW and the average load corresponding to the temperature trigger is estimated at 102 MW, the volume of the option is set equal to (102-100)*24*31 ≈ 1500 MWh. Likewise, the volume of the second option, whose trigger level is -9°C, would be the expected increase in monthly volume compared with the volume at the previous trigger level, and so on.

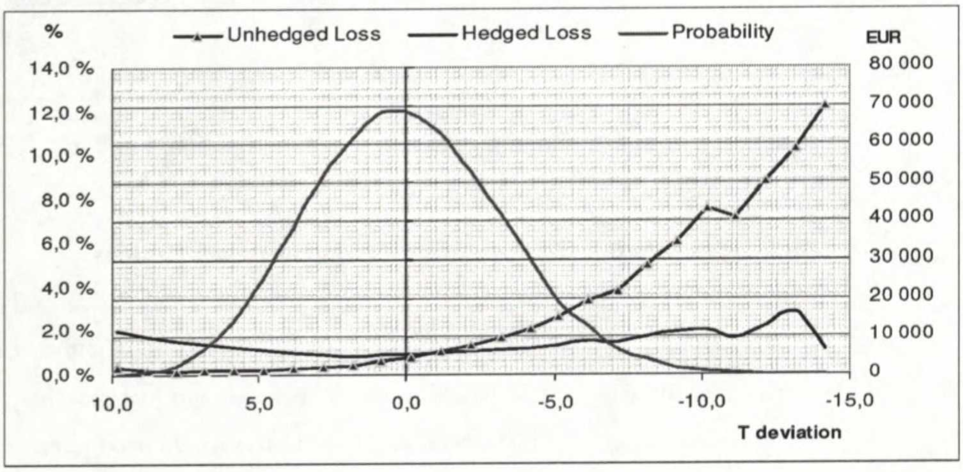


Figure 37: Hedging with monthly temperature-contingent options.

Figure 37 shows the result of such a hedge. Actually, the pure temperature-contingent option strategy left a gently sloping linear exposure and, consequently, it was complemented with an HDD swap with tick size at 1000. The hedging has reduced the variance of cash flows to merely 35 per cent of what it used to be. Again, the higher moments of the distribution remain largely unaffected.

Figure 38 examines the performance of the hedge from another perspective. It shows the probability weighted losses with and without hedging. The areas under the curves are equally large, but the hedged curve (rightmost) has changed its position and shape. As the probable loss curves illustrate the composition of the expected loss, it can been inferred from the figure that a larger part of the hedged losses are expected during warmer months and, conversely, colder months are not expected to produce that much losses anymore.

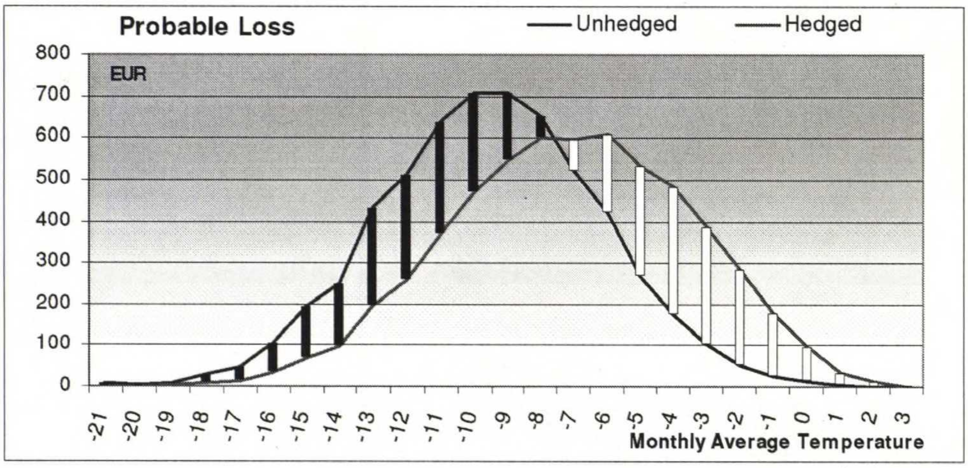


Figure 38: Probable loss curves.

Some points that have not been explained explicitly in this section still need to be made clear. First of all, the above strategies have been devised to get protection from exposure to temperature, while volumetric risk encompasses other factors, too. Furthermore, the simulations do not take account of those other risk factors that can have an effect on prices. For instance, the coincidence of cold weather and significant deficit in the hydrological balance can result in substantially larger losses, which are not fully covered by temperature hedges. Weather hedges that include more than one weather variable can be much more complex and are discussed in e.g. Dischel (2001).

Secondly, while the fair cost of the options is included also in the assessment of the second strategy, it is not their true fair cost. The payouts would in reality be larger, since the influence of other factors besides temperature results in greater price volatility[6]. As a matter of fact, temperature-contingent power options give protection from other factors affecting the severity of volumetric exposure, as well. This it not a bad thing, but must be kept in mind when estimating the fair price and appropriate hedge levels. Furthermore, the implication is that the overall results of this kind of hedge might look slightly different from figure 37. Particularly, the size of the HDD swap would need to be re-estimated.

[6] It is a well-established fact that the value of an option increases as volatility increases (e.g. Hull 2000, 170).

5.5 Recommendations

The feasibility of the presented alternatives to managing weather-induced volumetric risk was already discussed in section 5.4.1. To recap, some weather contracts, such as weather-linked bonds or catastrophic insurances, as well as traditional power options and forwards, were deemed unsuitable for current purposes. In contrast, group-wide concentration of the weather risk and internal hedging were considered more viable options, but the complexity and extent of such solutions might take plenty of time to implement. In addition, further study of the pros and cons of such an approach were left out from the scope of this thesis.

Based on what has been stated about the state of the weather market and the results of section 5.4.2, my recommendation would be to use the strategy of standard heating-degree day swaps and options as an initial approach to managing the exposure to temperature. The weather market was found to be still in its infancy and the liquidity of other than generally adopted simple weather contracts is poor. As a result, the risk premia demanded from more unorthodox structures can be very high. Furthermore, there is practically no way of reselling structured positions, whereas it is more likely that the better liquidity of standard products allows some adjustments to assumed positions. The recommended strategy performed quite satisfactorily in the simulation tests.

However, it might also be worthwhile to carry out an investigation to the availability of more structured hedges. Section 5.1 showed how daily temperature-contingent power options could be used to hedge volumetric risk almost perfectly. The key advantage of such options is that their payouts are sensitive to both temperature, which has been identified as the main determinant of customer load, and prices. What is more, section 5.4.2 demonstrated that also their monthly counterparts would perform pretty well. Naturally, other kinds of hedge structure could be thought of, too.

6 CONCLUSIONS

6.1 Summary

The aim of this thesis was to conceptually define volumetric risk, quantitatively analyse it and to propose a feasible means to levelling its effect on retailer profits. While many factors affect the severity of volumetric risk, this study was limited to temperature-induced volumetric risk only. The study was motivated by the great losses many Nordic retailers had to suffer in the cold winter of 2002/2003.

The thesis began with a thorough introduction to the Nordic electricity market and its functioning principles. The recent development of the legal framework was discussed and it was argued that liberalisation has highlighted the susceptibility of retailers profits to weather conditions. Chapter three, for its part, dealt with the weather market and some weather contract types. The conclusion was that the weather market is still in its infancy and only the most standard weather derivatives have some liquidity in Europe.

Subsequently, attention was shifted to the analysis of exposure to temperature, around which the rest of the study was centred. Volumetric risk was defined as the product of volume and price deviations from their expected values, i.e. $\Delta V^{*}\Delta P$. A retailer loses money when it needs to complement hedged procurement with high-priced spot electricity to fulfil its delivery obligations. Consequently, volumetric risk derives from the inability to accurately forecast demand, which in turn is largely determined by outdoor temperature. The exposure is exacerbated by the non-linear relationship between prices and load, which implies that it is greater at very cold times when both load and prices rise intensively.

Rookley (2000) discussed volumetric exposure and developed a model for its assessment. However, Rookley did not try to separate the different sources of the risk, such as temperature. Rookley also left the modelling of the expected spot price rather ambiguous. This thesis completed the analysis by employing regression analysis and joint simulation of prices and load. Temperature was used as the explanatory variable in the load equation and as a proxy for system load in the price equation. Furthermore, by including hydrological conditions, another major factor behind prices, as well as a few other independent variables, the pure influence of temperature could be isolated. A historical analysis revealed the highly non-linear nature of the exposure and the significant skew of the loss distribution.

Chapter four ended by performing a simulation analysis to better estimate the shape of the loss curve and to obtain confidence levels for the estimates. The outcome of the simulation supported the results of the historical analysis. Also, it was argued that monthly estimates could not be induced from the daily loss curve, which was attributed to the strong non-linearity. Monthly analysis was based on historical temperature realisations and showed results similar to those obtained on a daily level. Particularly, the risk related to cold temperatures was found to be significant, whereas deviations towards warmer conditions produced only negligent losses.

Next, approaches to managing the risk were discussed. The strategy of daily temperature-contingent power options was found to be the most realistic of ideal hedge structures. These dual-trigger options have the advantage of being sensitive to both temperature and prices. In addition, a group-wide aggregation of weather risk and internal exposure matching were considered as potential approaches that should be investigated. Conversely, some other strategies, such as using insurances or standard electricity derivatives, were deemed inappropriate.

Finally, the performance of two strategies using weather contracts was tested. The second strategy, which consisted of monthly temperature-contingent power options and an HDD swap, performed slightly better than the first strategy. However, the strategy of standard HDD swaps and options was recommended as an initial solution on grounds of potentially better liquidity for the more standard products. The performance of the standard weather products was found to be quite satisfactory, too. Nonetheless, looking into the availability of more exotic structures was also encouraged.

6.2 Validity and Reliability

Volumetric risk is rather complex, as numerous factors can influence supply and demand conditions. Yet, this study was limited to an investigation of the exposure to temperature alone. Therefore, some parts of the employed model, such as spot price simulation, are not universally valid, but only capture the properties essential to temperature exposure.

The more severe limitation of this work was that the used regression models had some deficiencies that could not be corrected. Above all, two problems were detected in the model residuals: heteroscedasticity and serial correlation. Serial correlation was strongly present in both models, while significant heteroscedasticity was found only in the spot price model. Some rudimentary correction methods were applied to both models, but they did not lead to any significant improvements. Since the study was not primarily an econometric one, more advanced correction methods were intentionally left out.

It was obvious that the problems of the spot price model could mostly be attributed to missing explanatory variables. On the other hand, the scarcity of load data prevented the use of smaller time resolution in the load model. Autocorrelation could probably have been reduced by running the regression separately for each month of a year. Nevertheless, autocorrelation or heteroscedasticity does not cause biasedness in the estimates, but rather makes them less efficient. Of course, the reliability of the results was slightly weakened because of these problems. The results were very robust, however, and I regarded them reliable enough to be used for practical purposes.

6.3 Applicability of Results

Company-specific load data and daily average prices for the price area Finland were used in the analysis, which implies that the results of this thesis are directly applicable to the case company. The only thing that restricts the applicability is that the performance analysis of weather hedges did not take account of real market quotations for the contracts, but it was assumed that the hedges could be bought at fair price. In reality, risk premia are demanded and their magnitude might cause some changes to the preferred hedging strategy.

In contrast, the results presented in this thesis are not directly applicable to other purposes, but must be reproduced with appropriate data. However, the developed methodology can be applied elsewhere, too, probably with quite minor modifications.

6.4 Future Research

Evidently, this study would be interesting to carry out with more abundant data resources. Company-specific load data would be required from several years to be able to reproduce the analysis with a monthly resolution instead of regressing the whole series together. In addition, if adequate data on system load were available, it would be possible to model prices directly without the need to resort to proxy variables. It would also be helpful to have data on all other factors affecting prices, such as fuel prices, plant outages and net import from surrounding countries. Furthermore, more advanced correction methods could be applied to rectify any remaining deficiencies in the model.

Apart from improving the quality of the analysis presented in this thesis, research on the influence of other weather variables could be done. For instance, a natural continuation of this study would be the modelling and quantification of precipitation risk. That would enable more precise estimation of volumetric exposure, as well. Another potential field of study would be the valuation of different kind of weather products. Being able to valuate the products is a prerequisite for any sort of trading activity. In addition, better knowledge and standardisation of the valuation methods would tighten the market and contribute to the liquidity of weather derivatives.

7 APPENDICES

7.1 Appendix 1 – Load Regression Results

Regression

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,986[a]	,973	,972	23,6260

a. Predictors: (Constant), Saturday, Feb, <-20C, Jun, Year2003, Jul, Sep, Sunday, Nov, Aug, Oct, Apr, May, Year2004, Mar, Jan, Temperature

b. Dependent Variable: Load

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	100,00	,68		147,32	,000
	Jan	12,31	,82	,131	14,99	,000
	Feb	6,85	,83	,070	8,28	,000
	Mar	-3,74	,83	-,040	-4,52	,000
	Apr	-12,20	,90	-,128	-13,57	,000
	May	-15,96	1,02	-,169	-15,61	,000
	Jun	-20,22	1,15	-,172	-17,51	,000
	Jul	-26,83	1,18	-,235	-22,77	,000
	Aug	-24,56	1,17	-,215	-21,00	,000
	Sep	-21,96	1,06	-,191	-20,63	,000
	Oct	-17,15	,91	-,152	-18,93	,000
	Nov	-7,21	,89	-,063	-8,08	,000
	Year2003	-12,72	,36	-,216	-35,20	,000
	Year2004	-24,01	,52	-,313	-46,51	,000
	Sunday	-2,35	,48	-,028	-4,94	,000
	<-20C	8,24	1,64	,033	5,01	,000
	Temperature	-1,94	,04	-,606	-48,50	,000
	Saturday	2,54	,48	,031	5,35	,000

a. Dependent Variable: Load

Notice that the results in the above table of coefficients have been scaled to hide the real load of Vattenfall. The scaling has been done so that the constant has received value 100. This has not changed the interpretation of the results in any way.

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17035778	17	1002104,562	1795,283	,000[a]
	Residual	479483,2	859	558,188		
	Total	17515261	876			

a. Predictors: (Constant), Saturday, Feb, -20C, Jun, Year2003, Jul, Sep, Sunday, Nov, Aug, Oct, Apr, May, Year2004, Mar, Jan, Temperature

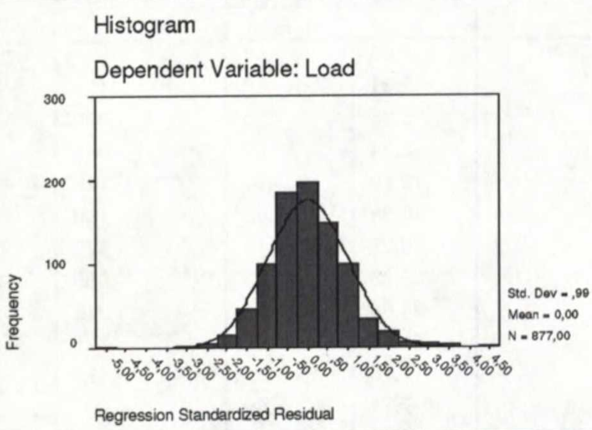
b. Dependent Variable: Load

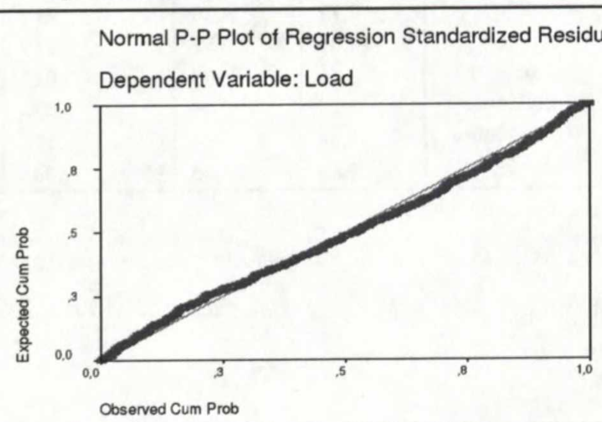
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	139,574	770,606	363,700	139,4533	877
Residual	-123,324	103,083	,000	23,3956	877
Std. Predicted Value	-1,607	2,918	,000	1,000	877
Std. Residual	-5,220	4,363	,000	,990	877

a. Dependent Variable: Load

Charts





Non-Parametric Tests

One-Sample Kolmogorov-Smirnov Test

		Unstandardized Residual	Standardized Residual
N		877	877
Normal Parameters[a,b]	Mean	,0000000	,0000000
	Std. Deviation	23,39562396	,99024927
Most Extreme Differences	Absolute	,039	,039
	Positive	,039	,039
	Negative	-,036	-,036
Kolmogorov-Smirnov Z		1,159	1,159
Asymp. Sig. (2-tailed)		,136	,136

a. Test distribution is Normal.

b. Calculated from data.

Autocorrelation (ACF)

```
Autocorrelations:   RES_1   Unstandardized Residual

      Auto- Stand.
Lag   Corr.   Err. -1  -.75  -.5 -.25   0   .25  .5   .75   1   Box-Ljung  Prob.
                    +----+----+----+----+----+----+----+----+
  1   ,590   ,034                     . .************              305,931   ,000
  2   ,321   ,034                     . .*****                     396,977   ,000
  3   ,273   ,034                     . .****                      462,540   ,000
  4   ,215   ,034                     . .***                       503,425   ,000
  5   ,169   ,034                     . .**                        528,688   ,000
  6   ,140   ,034                     . .**                        546,051   ,000
  7   ,191   ,034                     . .***                       578,425   ,000
  8   ,070   ,034                     . *                          582,817   ,000
  9 -,044    ,034                     * .                          584,537   ,000
 10 -,060    ,034                     * .                          587,712   ,000
 11 -,063    ,034                     * .                          591,285   ,000
 12 -,075    ,033                    *. .                          596,354   ,000
 13 -,037    ,033                     * .                          597,551   ,000
 14  ,009    ,033                     .*.                          597,629   ,000
 15 -,057    ,033                     * .                          600,496   ,000
 16 -,116    ,033                    *. .                          612,499   ,000

Plot Symbols:      Autocorrelations *     Two Standard Error Limits .

Total cases:   877    Computable first lags:   876
```

7.2 Appendix 2 – Price Regression Results

Regression

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,931[a]	,866	,865	,16417

a. Predictors: (Constant), <-20C, SUN, Y01, NOV, JUN, SEP, JUL, SAT, SURPLUS, OCT, Y02, FEB, AUG, APR, MAR, Y04, MAY, Y00, JAN, <-15C, Y03, Temperature

b. Dependent Variable: LOGSPOT

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,760	,016		173,043	,000
	Temperature	-,007	,001	-,145	-7,134	,000
	SURPLUS	-,022	,001	-,738	-39,714	,000
	JAN	-,071	,018	-,047	-3,865	,000
	FEB	-,109	,019	-,069	-5,769	,000
	MAR	-,143	,018	-,094	-7,749	,000
	APR	-,180	,020	-,117	-9,047	,000
	MAY	-,161	,022	-,105	-7,230	,000
	JUN	-,076	,025	-,045	-3,009	,003
	JUL	-,106	,026	-,063	-4,054	,000
	AUG	,062	,026	,037	2,424	,015
	SEP	,037	,023	,022	1,601	,110
	OCT	-,033	,020	-,020	-1,611	,107
	NOV	-,020	,019	-,012	-1,035	,301
	SAT	-,129	,011	-,102	-12,064	,000
	SUN	-,168	,011	-,132	-15,675	,000
	<-15C	-,006	,002	-,044	-3,077	,002
	Y00	,341	,014	,296	25,123	,000
	Y01	,420	,012	,366	33,693	,000
	Y02	,503	,013	,437	40,073	,000
	Y03	,317	,019	,275	16,294	,000
	Y04	,259	,021	,155	12,506	,000
	<-20C	-,007	,002	-,042	-3,294	,001

a. Dependent Variable: LOGSPOT

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	339,283	22	15,422	572,225	,000[a]
	Residual	52,446	1946	,027		
	Total	391,730	1968			

a. Predictors: (Constant), <-20C, SUN, Y01, NOV, JUN, SEP, JUL, SAT, SURPLUS, OCT, Y02, FEB, AUG, APR, MAR, Y04, MAY, Y00, JAN, <-15C, Y03, Temperature

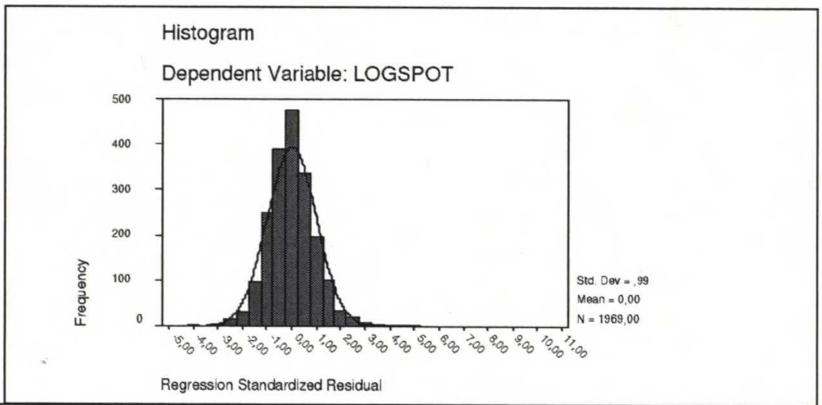
b. Dependent Variable: LOGSPOT

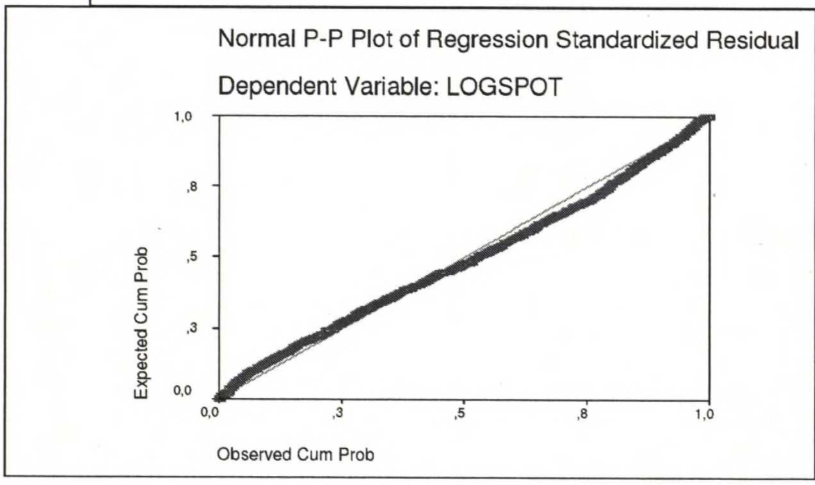
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,2036	4,5983	3,0342	,41521	1969
Residual	-,8136	1,7724	,0000	,16325	1969
Std. Predicted Value	-2,000	3,767	,000	1,000	1969
Std. Residual	-4,956	10,796	,000	,994	1969

a. Dependent Variable: LOGSPOT

Charts





Non-Parametric Tests

One-Sample Kolmogorov-Smirnov Test

		Unstandardized Residual	Standardized Residual
N		1969	1969
Normal Parameters[a,b]	Mean	,0000000	,0000000
	Std. Deviation	,16324707	,99439486
Most Extreme Differences	Absolute	,052	,052
	Positive	,052	,052
	Negative	-,033	-,033
Kolmogorov-Smirnov Z		2,303	2,303
Asymp. Sig. (2-tailed)		,000	,000

a. Test distribution is Normal.

b. Calculated from data.

Autocorrelation (ACF)

```
Autocorrelations:   RES_1   Unstandardized Residual

     Auto- Stand.
Lag  Corr.   Err. -1  -.75   -.5 -.25   0   .25  .5   .75   1   Box-Ljung  Prob.
                   |----|----|----|----|----|----|----|----|
  1  ,657   ,023                       . |.************           850,411   ,000
  2  ,521   ,023                       . |.*********             1384,965   ,000
  3  ,452   ,023                       . |.********              1788,252   ,000
  4  ,405   ,023                       . |.*******               2112,444   ,000
  5  ,365   ,022                       . |.******                2375,499   ,000
  6  ,370   ,022                       . |.******                2646,484   ,000
  7  ,379   ,022                       . |.*******               2930,177   ,000
  8  ,309   ,022                       . |.*****                 3119,719   ,000
  9  ,252   ,022                       . |.****                  3245,904   ,000
 10  ,222   ,022                       . |.***                   3343,574   ,000
 11  ,213   ,022                       . |.***                   3433,826   ,000
 12  ,195   ,022                       . |.***                   3509,028   ,000
 13  ,210   ,022                       . |.***                   3596,483   ,000
 14  ,207   ,022                       . |.***                   3681,916   ,000
 15  ,170   ,022                       . |.**                    3739,631   ,000
 16  ,126   ,022                       . |.**                    3771,107   ,000

Plot Symbols:       Autocorrelations *     Two Standard Error Limits .

Total cases:  1969     Computable first lags:  1968
```

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